In the Name of God

Journal of
Information Systems & Telecommunication
Vol. 13, No.2, April-June 2025, Serial Number 50

Research Institute for Information and Communication Technology
Iranian Association of Information and Communication Technology
Affiliated to: Academic Center for Education, Culture and Research (ACECR)

Print ISSN: 2322-1437
Online ISSN: 2345-2773
Publication License: 91/13216
Editorial Office Address: No.5, Saeedi Alley, Kalej Intersection., Enghelab Ave., Tehran, Iran,
P.O.Box: 13145-799 Tel: (+9821) 88930150 Fax: (+9821) 88930157
E-mail: info@jist.ir , infojist@gmail.com
URL: jist.acecr.org

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Publisher:
Iranian Academic Center for Education, Culture and Research **(ACECR)**

This Journal is published under scientific support of
Advanced Information Systems (AIS) Research Group and
Telecommunication Research Group, ICTRC

Acknowledgement

JIST Editorial-Board would like to gratefully appreciate the following distinguished referees for spending their valuable time and expertise in reviewing the manuscripts and their constructive suggestions, which had a great impact on the enhancement of this issue of the JIST Journal.

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Vol.13, No.2, April-June 2025, 77-90

http://jist.acecr.org
ISSN 2322-1437 / EISSN:2345-2773

Linearity Enhanced Noise Cancelling Low Noise Amplifier for Ultra-Wideband Application

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Received: 01 Feb 2024/ Revised: 04 Apr 2025/ Accepted: 04 May 2025

Abstract

The Low Noise Amplifier (LNA) stands as a crucial element RF receiver chain, demanding a delicate interplay of characteristics such as high gain, low noise figure (NF), superior linearity, and an extensive dynamic range. De-signing an ultrawideband (UWB) LNA poses a complex challenge as engineers grapple with intricate trade-offs inherent in these parameters. To address these challenges, noise cancellation techniques have emerged as valuable tools, revolutionizing the design of UWB LNAs by relaxing the traditional trade-off between bandwidth and input matching. This innovative approach not only enhances bandwidth but also effectively cancels out the un-desirable noise and nonlinearities from the input MOSFET. Despite the advancements afforded by noise cancellation, the broad bandwidth of UWB LNAs presents a significant hurdle. If the linearity is insufficient, the UWB LNA faces performance degradation due to increase in-band interference. In response, this article proposes an inventive linearization technique, a combination of Noise Cancelling (NC) and complementary derivative super-position (CDS), aiming to increase the linearity of UWB LNAs. Through meticulous simulations conducted using Cadence Virtuoso with GPDK090 library, the proposed LNA showcases impressive performance metrics across the UWB spectrum. Notably, it achieves a gain ranging from 12.5 dB to 15.5 dB, a noise figure within the range of 3.9 dB to 5.26 dB, and an IIP3 spanning from 6.3 dBm to 8.8 dBm. Remarkably, this innovative LNA accomplishes these feats while operating with a modest power consumption of 11.36 mW from a 1.2 V supply. This groundbreaking technique holds promise for significantly enhancing the efficiency and overall performance of UWB LNAs within contemporary RF receiver systems.

Keywords: Noise Cancellation; LNA-Low Noise Amplifier; CM-Current Mirror; CG-Common Gate; Linearity; Complementary; UWB-Ultrawideband.

1- Introduction

The rapid progress in communication technology necessitates fast data transmission, high-speed connectivity, and extensive bandwidth. To meet these demands, it is crucial to develop wideband RF frontends capable of supporting multiple frequency bands. Consequently, research efforts are being directed toward designing low noise amplifiers that can effectively operate across wide frequency ranges. Several researchers have put forward designs for wideband low noise amplifiers (LNAs) intended for the (3.1 GHz to 10.6 GHz) [1]–[7]. However, these LNAs often involve multiple trade-offs between desirable features such as high gain, high linearity, low noise figure, input matching, and low power consumption. Consequently, achieving a well-rounded LNA design that incorporates all these features is a challenging task [8]. For instance, while it is possible to attain high gain and low noise figure in an LNA, it typically comes at the expense of increased power dissipation, making the ultrawideband LNA power-hungry [9]. Wideband matching can be accomplished by using inductors, but this approach requires a significant amount of physical area [2]– [4] [6].

1-1- Sate of Art

To designing wideband LNAs, the most employed topologies are CG and Common CS with resistive feedback. However, these topologies often face trade-offs between input matching and NF or having a low gain and high-power dissipation. In CS with resistive feedback, the inclusion of a feedback resistor introduces extra noise and also restricts

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gain in wide-band applications [10], [11][12]. Achieving wideband input matching can be accomplished in the CG-LNA, but it comes at the expense of high-power dissipation. To address this trade-off, gm-boosting of the input device is suggested in [13]. However, the noise introduced by the gm-boosting stage results in an increased NF. NC is a commonly employed technique in wide-band LNAs, aimed at reducing input device noise by utilizing an auxiliary device, however this noise re-duction trade-off with power consumption [1-23]. To reduce the noise and power consumption of the auxiliary device in NC, two approaches, namely, dual-NC and current reuse, are introduced in [23] and [9], respectively.

1-2- Motivation

The wide bandwidth of UWB LNA permits the entry of numerous in-band interferences. In cases where the LNA's linearity is insufficient, this leads to the 2nd - 3rd order intermodulation, cross modulation, harmonic distortion (HD) and gain compression (P1dB) collectively degrade the LNA performance. Thus, LNA linearity becomes a crucial parameter, and it is defined by the input 2nd - and 3rd -order intercept points (IIP2 and IIP3). The distortion within the LNA follows a similar path as noise in an NC-LNA. Therefore, the distortion of the input device is also mitigated in the same manner as noise in an NC-LNA [1-23]. In NC-LNAs, an auxiliary device is employed to cancel the noise of the input device, forming the cascade structure in the LNA. However, in cascade structure, the presence of parasitic capacitance can lead to a degradation in linearity due to second-order interactions. Recently reported linearization techniques in [10] and [19] trade-off with bandwidth. In [17], various wideband linearization techniques are explored, and it is suggested that the integration of multiple techniques can result in better linearization. Among these techniques, CDS employs NMOS and PMOS transistors to enhance IIP3 without affecting IIP2. This method enhances linearity over a range of bias voltages rather than at a single point. Typically, the optimal biasing voltages for optimizing IIP2 and IIP3 are dis-tinct, leading to the achievement of only one optimal condition.

In this article, a hybrid linearization approach is presented, which combines NC and CDS techniques. In the CG-gm boosted NC-LNA with CM combination network, CDS is employed at both the input and gm-boosting stages to mitigate the 2nd -order interactions present in NC-LNA. This leads to enhanced linearity performance across the entire UWB spectrum.

2- Overview Of Existing NC-LNA

Low-noise amplifier's noise-cancelling principle is shown in Fig. 1, where source impedance is denoted by R_S. The idea behind noise cancellation is to locate two nodes (G and H) in the circuit where the signal and input transistor noise occur with different polarities. By using proper scaling and summation, the output signal is increased while the noise is reduced.

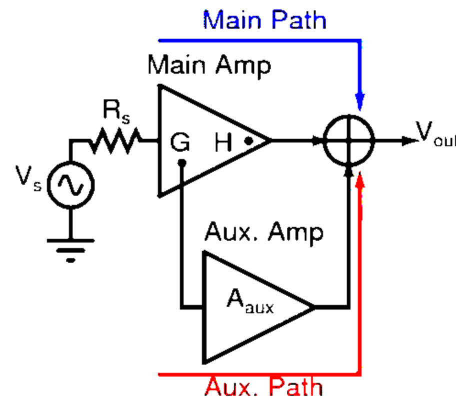
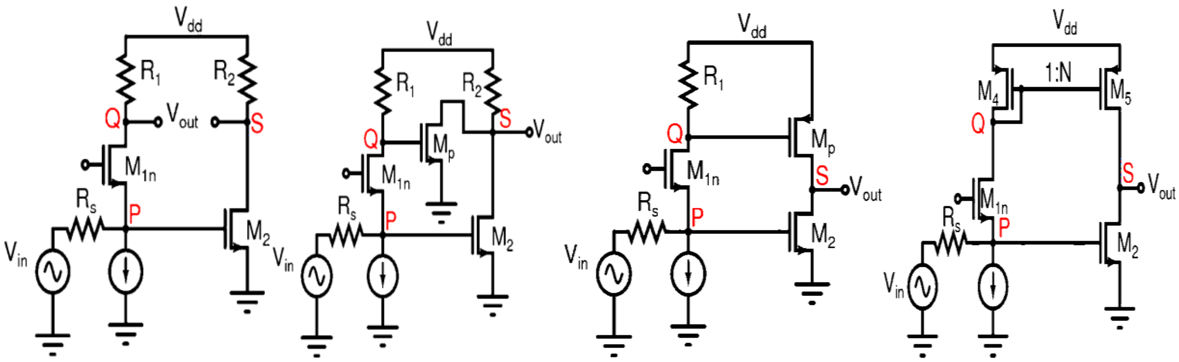


Fig. 1 Noise Cancelling Principle [8]

The CS with resistive feedback and the CG-CS topologies are the two basic ways to accomplish noise cancelling. The first topology is not well-suited for UWB applications because it exhibits limited gain and introduces higher levels of noise due to the presence of the feedback resistor [11]. The CG-CS topology provides better gain and wideband input matching than the CS with resistive feedback, making it appropriate for UWB applications [19],[25],[26]. There are numerous known NC-LNA variations based on the CG-CS topology that fall under the following categories are shown in Fig. 2. A differential output NC-LNA based on the CG-CS topology is proposed in [24], but there are numerous trade-offs between gain, bandwidth, and Noise Figure (NF). By adding another NMOS in the main path, which senses voltage and converts it to current, differential output LNA can be converted to single ended LNA to eliminate these trade-offs [17]. To obtain the current reuse output of the LNA, NMOS is substituted by PMOS in [19]. when converting a differential output to a single-ended output, the inclusion of NMOS/PMOS introduces inherent distortion, thereby compromising the linearity of the LNA. To tackle this issue, a current mirror with a mirroring ratio of N is utilized to add the signal at the output in current mode. This approach eliminates the need for voltage-to-current conversion, resulting in a reduction in distortion when compared to other CG-CS LNA [20]–[22]. The NC-LNA with current mirror combination network has input to output transconductance that is N times greater than the typical CG-CS NC LNA, which permits higher gain bandwidth products (GWB), making the NC-LNA with CM appropriate for ultrawideband applications. In NC-LNA with CM, input device's noise/distortion is cancelled at the output when the noise cancellation condition ($N = g_{m2}R_s$) is satisfied.



(a) (b) (c) (d)

Fig. 2 (a) Differential LNA [23] (b) CG-CS single ended LNA with NMOS [16] (c) CG-CS current reuse single ended LNA [18] (d) CM-based Conventional CG-CS NC LNA [1, 5] , [19–21]

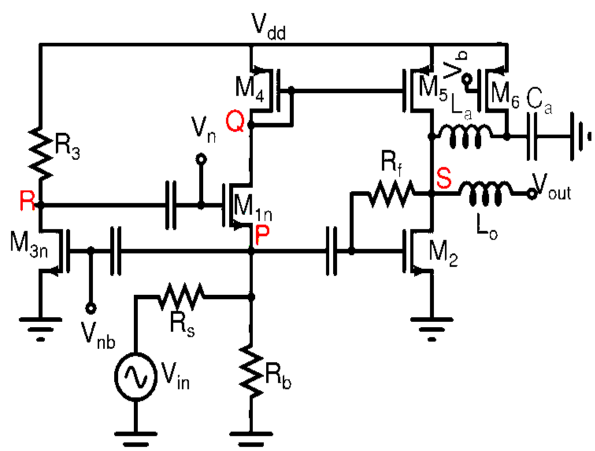


Fig. 3 g_m Boosted CG-CS-LNA incorporating a Current Mirror (CM) [5]

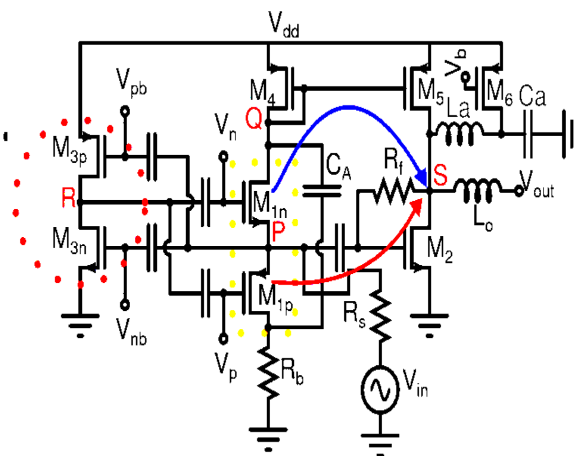


Fig. 4 Proposed CM-based CG-CS NC LNA

Additionally, the noise from transistors M_5 and M_2 can be minimized by raising the current mirroring ratio N. The remaining noise originating from M_4 in this LNA can be mitigated by decreasing g_{m4}. However, the requirement to achieve wideband input matching mandates that g_{m1} be set to 20ms, resulting in a higher current demand from M_{1n}. Since M_4 shares this same current with M_{1n}, it becomes impractical to reduce g_{m4}, ultimately designating M_4 as the primary source of noise [20]. In [1] a solution is proposed to decrease the noise from M_4 and enhance input matching flexibility. This is achieved by boosting g_m in M_{1n}, and to meet the Noise-Canceling (NC) condition, a current bleeding MOSFET (M_6) is introduced. In [5], a passive network is suggested to attenuate the noise contribution from the current bleeding MOSFET (M_6) at higher frequencies as shown in Fig. 3. Although the NC-LNA in [1], [5] offers excellent gain and noise figure, it suffers from linearity. Maximum linearity achieved in [1], [5] is -2.8 dBm @ 6 Ghz in whole UWB.

From the analysis presented earlier, it can be observed that the NC-LNA with CM exhibits the lowest distortion compared to other CG-CS NC-LNA configurations. This is because the signals are directly merged in current mode at the output. In prior works such as [1] and [5], UWB LNAs with CM have been proposed. However, their linearity is compromised, mainly due to second-order interactions. This article focused on improving the linearity of NC-LNA with CM combination network by using novel hybrid linearization technique.

3- Methods

3-1- Design Methodology

Designing a proposed wideband LNA presents several challenges, including broadband input matching and maintaining a flat gain across the frequency band. These difficulties arise due to variations in impedance and MOSFET transconductance as a function of frequency. Additionally, implementing the proposed LNA in the GPDK090 technology node introduces further challenges, such as achieving low noise and high linearity, due to the limitations of lower supply voltage and parasitic capacitance. However, the lower supply voltage helps reduce power dissipation. Despite these challenges, the higher cutoff frequency of GPDK090 makes it a viable choice for designing UWB LNA. Parasitic capacitance is characterized through S-parameter simulation. To mitigate its effects, an inductor (L_1) is placed at input to achieve wideband input matching, while two inductors ($L_a$and L_o) are placed at the output node, reducing the noise contribution of M6 and improving gain flatness across the entire bandwidth.

Implementation of the CG-CDS configuration with noise of NMOS (M_n) and PMOS (M_p) is shown in Fig. 5(a) and Fig. 5(b) respectively. while Fig. 5(c) shows the total noise of the CG complementary configuration. Capacitor C_A in Fig. 5(c) is employed to establish the AC equivalent drain node of the CG-CDS.

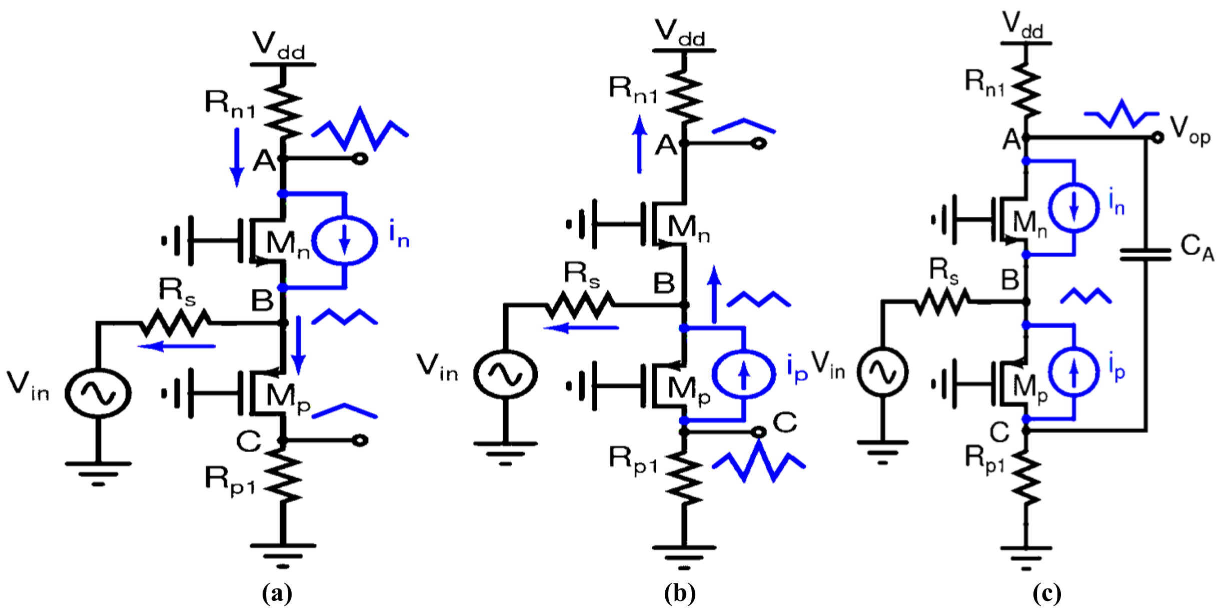


Fig. 5 (a) Noise of M_n (b) Noise of M_p (c) Toal noise in complementary common gate stage

At lower frequencies, C_A exhibits a high impedance, effectively isolating the drains of M_n and M_p, creating two separate stand-alone CG amplifiers. However, at higher frequencies, the low impedance of C_A establishes an AC equivalent drain node. Consequently, the distortion current of M_n loops back through the path of M_n-M_p-C_A-M_n. Due to the opposite g'_m profile (Fig. 7) of M_n and M_p , M_p effectively absorbs the distortion current from M_n, leading to enhanced linearity. This can also verify mathematically as in a complementary configuration, the AC input signals for NMOS and PMOS transistors are out of phase. As a result, the nonlinear output currents for NMOS (i_{dsn}) and PMOS (i_{dsp}) can be expressed as follows.

$$i_{dsn} = g_{1n}V_{gs} + g_{2n}{V_{gs}}^2 + g_{3n}{V_{gs}}^3 \quad (1)$$

$$i_{dsp} = -g_{1p}V_{gs} + g_{2p}{V_{gs}}^2 - g_{3p}{V_{gs}}^3 \quad (2)$$

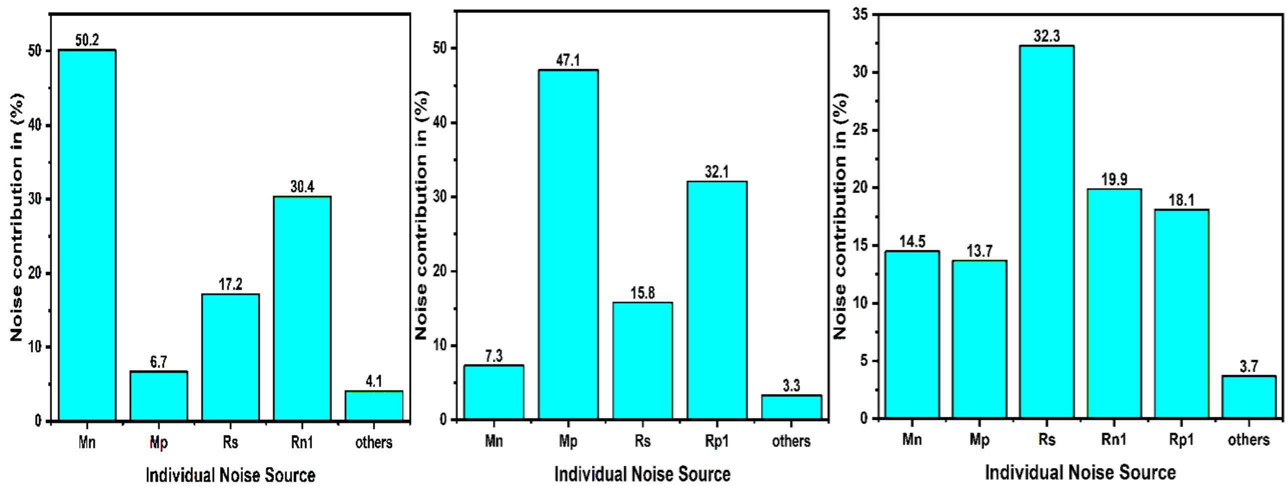
The total output current (i_{out}) of the complementary configuration is then given by:

$$i_{out} = i_{dsn} - i_{dsp} = (g_{1n} + g_{1p})V_{gs} + (g_{2n} - g_{2p}){V_{gs}}^2 + (g_{3n} + g_{3p}){V_{gs}}^3 \quad (3)$$

As shown in Equation 3, the second-order nonlinear coefficients (g_{2n}, g_{2p}) are subtracted at the output (Fig. 7), leading to an increase in second-order nonlinearity. Meanwhile, the third-order nonlinear coefficients (g_{3n}, g_{3p}) are added with opposite signs, resulting in a reduction of third-order nonlinearity. Consequently, the complementary configuration enhances both second- and third-order linearity.

In the presence of C_A, the percentage noise contribution from NMOS and PMOS in the CG-CDS configuration is reduced, when compared to the noise contribution at points A and B without C_A as shown in Fig. 6. In conclusion, CDS techniques can enhance linearity while also helping to reduce device noise to a certain extent.

Based on this, proposed CG-CS noise cancelling LNA in this study incorporates an active feedforward stage that replaces R_3 in Fig.3 with a PMOS transistor (M_{3p}) and introduces a PMOS transistor (M_{1p}) in the input stage to form CDS configuration as shown in Fig. 4. The cascade structure for noise cancellation can reduce linearity due to a 2nd -order interaction caused by parasitic capacitance. CDS has the capability to diminish 2nd -order interactions by lowering the 2nd-order nonlinearity coefficient of input stage. The main path incorporates a current mirror combiner (M_4 and M_5), while the NC path contains a common source stage (M_2). Additionally, a current bleeding circuit (M_6) and a biasing resistor (R_b) are utilized, where R_b can be replace with an inductor or a current source.



(a) (b) (c)

Fig. 6 Noise contribution in Fig. 5(c) at (a) Point A without CA (b) At Point B without C_A

The CM load merges the output signals originating from main and NC paths. To achieve the AC equivalent node of the complementary CG input stage (M_{1n} and M_{1p}), capacitor C_A is employed. This capacitor combines the out-of-phase noise voltages of M_{1n} and M_{1p}, leading to partial noise cancellation within the complementary CG stage. Any remaining noise of CG-CDS stage will be eliminated at the output when the noise cancellation criteria is satisfied.

The circuit operates as follows: The complementary g_m boosting stage provides input matching flexibility as well as reducing the current through M_1 and M_4. This reduction in current through M_4 lowers the gm4 results in improved noise figure and lower power dissipation. When the current through M_4 is reduced, the mirrored current through M_5 and M_2 is also reduced. This current reduction through M_2will result in a decreased g_{m2}, which will exacerbate the NC condition ($N = g_{m2}R_s$). To satisfy the NC condition, typically large g_{m2} is required. To tackle this issue M_6 is added to bleed the DC current and boost the g_{m2} [1]. However, the addition of M_6 introduces noise at higher frequencies. To address this issue, a passive network consisting of a capacitor (C_a) and an inductor (L_a) is placed at the drain terminal of M_6 [5]. Presence of parasitic capacitance at output node (S) reduce the gain at higher frequencies. To prevent this reduction in gain and to increase bandwidth, in proposed circuit includes the implementation of series peaking technique by adding inductor (L_o) at node S [15].

3-2- Input Matching and Gain

Ultra-Wideband (UWB) LNA operate over a wide frequency range (3–10 GHz), making conventional power matching challenging across all frequencies. Instead of focusing on input matching at a single frequency, the design aims to minimize reflections across the entire band to maintain stable performance.

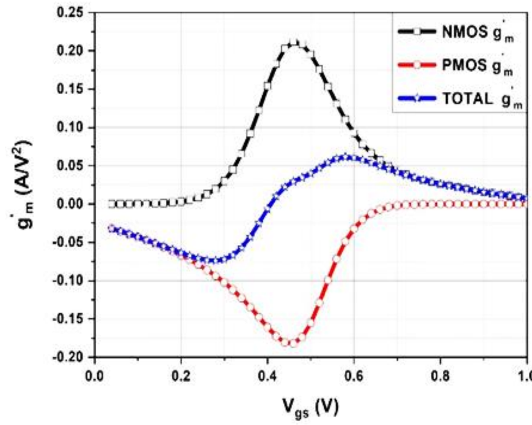


Fig. 7 g'_m profile of complementary CG stage in Fig. 5(c)

The input impedance of the suggested circuit can be represented in the following manner:

$$R_{in} = \frac{1}{g_{m1}(1+g_{m3}r_{o3})} \tag{4}$$

Where

$$r_{o3} = r_{on3}||r_{op3} \tag{5}$$

$$g_{m1} = g_{m1n} + g_{m1p} \,\&\, g_{m3} = g_{m3n} + g_{m3p} \tag{6}$$

The proposed circuit introduces a complementary g_m-boosting stage, which modifies the input impedance characteristics compared to conventional CG-CS LNAs with CM (Fig. 2(d)). Instead of relying solely on g_{m1}, the input impedance now depends on g_{m1}, g_{m3}, and ro_3. Consequently, achieving a 50-ohm input impedance is easily attainable by reducing the value of g_{m1} while increasing g_{m3} and ro_3. This adjustment allows for a reduction in current in the main branch, resulting in lower noise and power dissipation.

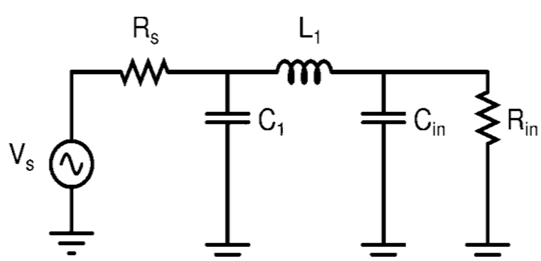


Fig. 8 π input matching [24]

Attaining effective impedance matching over a broad frequency range, particularly at higher frequencies, can be challenging due to the presence of parasitic capacitance within the input transistor. To address this challenge, the proposed circuit incorporates a π-type matching network, as shown in Fig. 8.

In Fig.8, C_{in} represents the input parasitic capacitance, while R_{in} corresponds to the impedance seen at the input of the proposed LNA. The π-type input matching network is implemented by including L_1 and C_1 components to form the necessary configuration. By using π-type matching, the circuit ensures that S_{11} remains below 10 dB across the entire ultra-wideband range. This enables effective impedance matching and maintains desirable performance throughout the entire frequency spectrum. The expression for the impedance of a π match can be formulated as.

$$Z_{in} = \frac{L_1 C_{in} R_{in} S^2 + L_1 S + R_{in}}{L_1 C_1 C_{in} R_{in} S^3 + L_1 C_1 S^2 + (C_1 + C_{in}) R_{in} S + 1} \tag{7}$$

From equation.7 wideband matching can be easily accomplished by careful optimization of the values of L_1 and C_1. The variation in L_1 and C_1 and corresponding S_{11} is shown in Fig. 13.

In Proposed circuit, gain between node P and S can be calculated by aggregating contributions from two distinct paths. In first path, input signal at node P experiences inverse amplification, resulting in an amplified signal at node R. Leveraging the substantial gate swing at the input of M_{1n}, a signal current corresponding to this is produced at node Q. This signal current is then replicated by the current mirror (CM) in the main path at a ratio of N. Simultaneously, the second (auxiliary) path directly transforms the input signal at node P into a corresponding signal current by utilizing the auxiliary CS stage. Ultimately, the two signal currents are merged at the output.

Hence, the mathematical representation of the gain from node P to node S can be expressed as:

$$A_v = -(Ng_{m1}(1 + g_{m3}ro_3) + g_{m2})R_L \tag{8}$$

The parallel output resistance r_o of transistors M_2, M_5, and M_6 contributes significantly to the overall load resistance R_L.

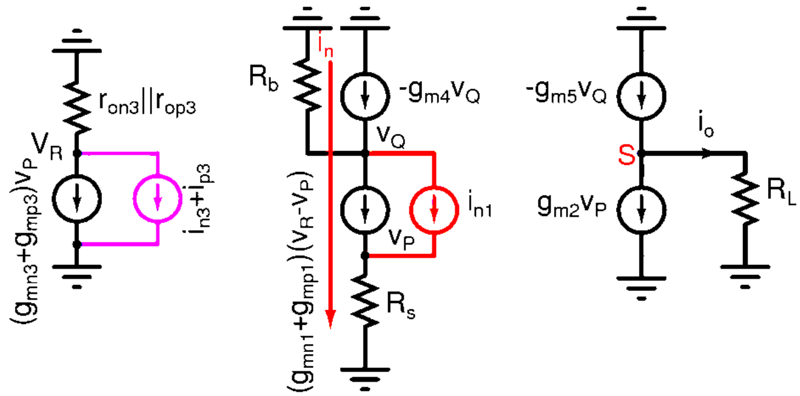


Fig. 9. Small signal modeling for analyzing noise in the suggested LNA

3-3- Noise Cancellation

The small-signal model for noise analysis of the proposed circuit is depicted in Fig. 9. Following the partial noise cancellation within the complementary common gate stage, the noise current i_n originating from the complementary input stage gives rise to two noise voltages at nodes P and Q, exhibiting opposite polarities. Similarly, the noise current produced by the complementary g_m-boosting pair also generates noise voltages at nodes P and Q with opposite polarities. If these two noise voltages of opposite polarities are suitably adjusted in scale and then combined at the output, it becomes theoretically feasible to eliminate the noise originating from both the input and g_m-boosting stages.

Mathematically, this can be expressed as follows at the output node (S) in Fig. 9.

$$g_{m5}v_P + g_{m2}v_Q = 0 \tag{9}$$

where, v_P and v_Q represent the noise voltages at nodes P and Q, respectively. The condition for noise cancellation can be achieved by solving Equation 9 using KCL at node v_R, v_P and v_Q.

$$g_{m2} = [g_{m1}(1 + g_{m3}r_{o3})]\, g_{m5}\left(\frac{1}{g_{m4}}||r_{04}||R_b\right) \tag{10}$$

Where r_{04} is the output resistance of M_4. Equation.10 can be rewritten as

$$g_{m2}R_s = g_{m5}\left(\frac{1}{g_{m4}}||r_{04}||R_b\right) \tag{11}$$

Where

$$R_s = \frac{1}{g_{m1}(1+g_{m3}r_{o3})} \tag{12}$$

Equation.11 suggests that actual noise cancellation occurs at $g_{m2} < (g_{m5}/g_{m4}\, R_s)$ due to parallel resistance of r_{04} and R_b. To evaluate the influence of R_b on NF, a set of NF plots was created for different R_b values, illustrated in Fig. 10. Analyzing this plot allows us to determine the optimal R_b value that minimizes the NF. By considering only the channel thermal noise of MOSFETs under NC condition, the noise factor of the proposed circuit can be expressed as follows:

$$NF = 1 + \frac{\Upsilon}{N} + \Upsilon g_{m4}R_s + \frac{\Upsilon g_{m4}R_s}{N} + \frac{\Upsilon g_{m6}R_s}{N^2} \tag{13}$$

The 2nd term corresponds to the noise associated with M_2. The 3rd and 4th terms represent the noise contributions from M_4 and M_5, respectively. Reducing g_{m4} can help to reduce the noise contribution of M_4 and M_5. The

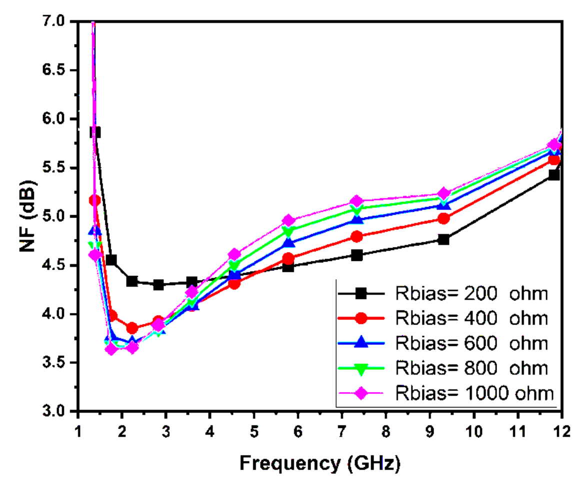


Fig. 10. NF for different value of R_b

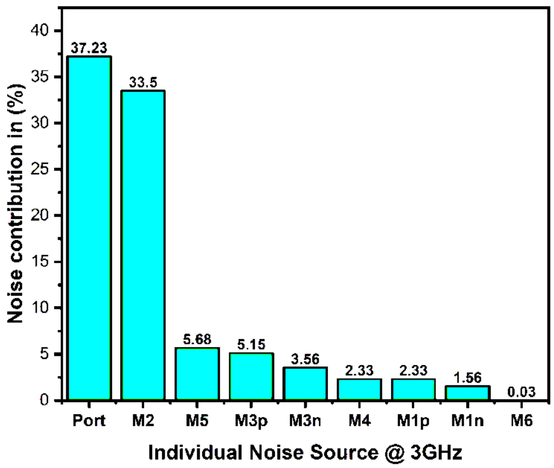


Fig. 11 Individual Noise contribution of Proposed LNA @ 3 GHz

last term denotes the noise introduced by M_6, and this noise can be reduced by employing a smaller g_{m6} and increasing the value of N. Fig. *11* illustrates the noise contributions of individual devices of proposed LNA. From this graph, after the noise cancellation, the primary source of noise is the auxiliary device (M_2). Under the noise cancellation condition, the noise from the input devices (M_{1n} and M_{1p}) and the gm-boosting stage (M_{3n} and M_{3p}) is effectively eliminated at the output. However, the inclusion of (M_{1p} and M_{3p}) to form the complementary pair introduces their own noise, which degrade NF of the proposed LNA.

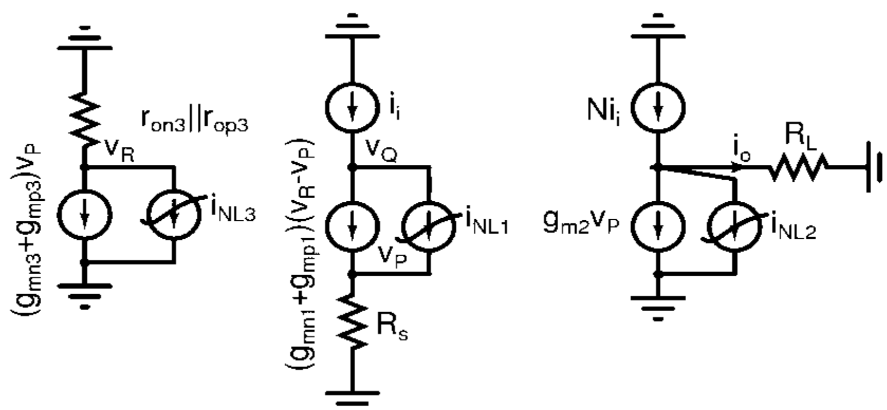


Fig. 12 Small signal modeling for evaluating distortion in the suggested LNA.

3-4- Distortion Cancellation

The nonlinearity exhibited by MOSFET can be characterized as a current source governed by V_{gs} and V_{ds} coupled to the drain and source terminals [18]. Neglecting the g_{ds}-induced nonlinearity due to output conductance.

The Taylor series can be used to depict the current source as a function of v_{gs}

$$\mathrm{i_{ds}} = \mathrm{g_m v_{gs}} + \frac{\mathrm{g'_m}}{2!}\mathrm{v_{gs}^2} + \frac{\mathrm{g''_m}}{3!}\mathrm{v_{gs}^3} + \cdots \tag{14}$$

Where

$$\mathrm{g'_m} = \frac{\partial^2 \mathrm{I_{ds}}}{\partial\, \mathrm{V_{gs}^2}},\ \mathrm{g''_m} = \frac{\partial^3 \mathrm{I_{ds}}}{\partial\, \mathrm{V_{gs}^3}} \tag{15}$$

In Fig. *12*, a small signal equivalent circuit is illustrated for distortion analysis of the proposed circuit with nonlinear current i_{NL1} , i_{NL2} , i_{NL3} of MOSFET M_1 , M_2 and M_3 respectively. From small signal Model, output current at node S can be written as:

$$\mathrm{Ni_i} = \mathrm{i_o} - \mathrm{i_2} \tag{16}$$

By using KCL at node v_R and v_P in a small signal equivalent circuit for distortion analysis (Fig. *12*) i_o can be obtained in terms of v_{in} as:

$$\mathrm{i_o} = -\mathrm{g_{m2}v_{in}} - \mathrm{g_{m2}b_1^2v_{vin}^2} - (2\mathrm{g_{m2}b_1b_2} + \mathrm{g_{m2}b_1^3})\mathrm{v_{vin}^3} \tag{17}$$

Where

$$\mathrm{b_1} = \frac{1}{\mathrm{a_1}} \text{ and } \mathrm{b_2} = -\frac{\mathrm{a_2}}{\mathrm{a_1^3}} \tag{18}$$

Where

$$a_1 = (g_{m1}(g_{m3}R_3 + 1)R_s + 1) \quad (19)$$

$$a_2 = \frac{1}{2}R_s(g_{m1}\mathbf{g'_{m3}}R_3 - \mathbf{g'_{m1}}(g_{m3}R_3 + 1)^2) \quad (20)$$

From the output current equation.17,3rd -order input intercept point (IIP_3) can be expressed as follows.

$$IIP3 = \sqrt{\frac{4}{3}\left|\frac{g_{m2}}{2g'_{m2}b_1b_2 + g''_{m2}b_1^3}\right|} \quad (21)$$

$$2g'_{m2}b_1b_2 = 2g'_{m2} \times \left(-\frac{\frac{1}{2}R_s(g_{m1}g'_{m3}R_3 - g'_{m1}(g_{m3}R_3+1)^2)}{((g_{m1}(g_{m3}R_3+1)R_s+1))^4}\right) \quad (22)$$

Where

$$g'_{m3} = g'_{m3n} + g'_{m3p} \quad (23)$$

$$g'_{m1} = g'_{m1n} + g'_{m1p} \quad (24)$$

The Equation.21 for IIP3 clearly demonstrates that it depends on the 2nd and 3rd order nonlinearities (g'_{m2} and g''_{m2}) of the auxiliary CS stage M_2. By minimizing these nonlinearities, the IIP3 can be improved. The first term in the denominator of the IIP3 Equation, $2g'_{m2}b_1b_2$, it becomes evident that b_2 is dependent on g'_{m3} and g'_{m1} (Equation.18 & 20). However, in the proposed circuit, complementary input and g_m-boosting stage leads to reduction in g'_{m3} and g'_{m1} . This reduction in g'_{m3} and g'_{m1} directly contributes to an enhanced IIP3 for the circuit.

4- Results

To ensure a fair comparison of the proposed circuit, the g_m-boosted CG-CS LNA incorporating a Current Mirror (CM) (Fig. 3.) and the proposed circuit (Fig. 4.) were simulated using Cadence Virtuoso with GPDK090 nm CMOS process technology. In Table. 1 parameters comparison is provided for the suggested LNA and the g_m-boosted CG-CS LNA. The results reveal a noteworthy enhancement in IIP3, although there is a minor decline in terms of gain, power dissipation, and noise figure. As depicted in Fig. 13., for π-type input matching, the values of L_1 range from 0.7nH to 1nH. Increasing the value of the inductor leads to improved input matching. In the case of the proposed circuit, a value of 1nH was chosen for L_1 because it ensures that S_{11} remains below -10dB across the entire ultrawide band. Fig. 14. illustrates the comparison of gain between the proposed circuit and the g_m-boosted CG-CS LNA incorporating a Current Mirror (CM).

Table 1 Performance comparisons of two configurations

	Gm boosted NC-LNA with CM combination network (Fig. 3)	**Proposed LNA (Fig.4)**
Biasing condition	Resistor	Resistor
Frequency Range (Ghz)	3.1 to 10.6	3.1 to 10.6
S_{21} (dB)	16.8-23.8	12.5-15.5
NF (dB)	3.2-5.5	3.9 to 5.26
IIP3(dBm)	-4.5 to 4.3	6.3 to 8.8
Power (mW)	9	11.36

The gain of the suggested circuit is slightly lower than that of the g_m-boosted CG-CS LNA. In the entire ultrawideband range, the gain of the proposed circuit ranges between 12.5 dB and 15.5 db.

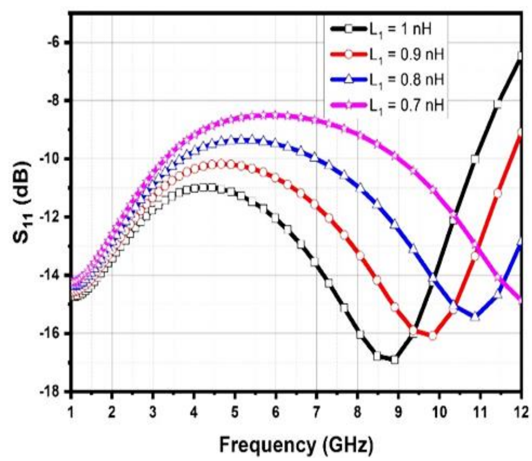


Fig. 13. S11 for Different Value of L_1

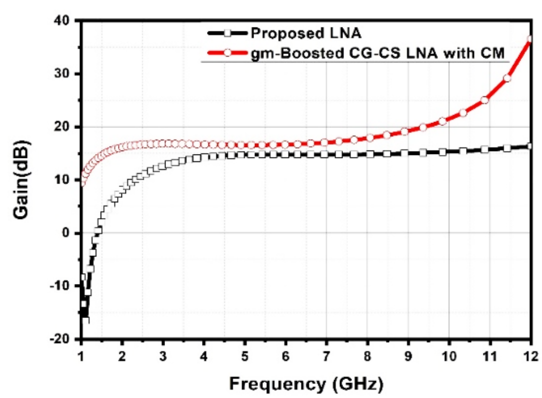


Fig. 14. Gain S_{21} (dB)

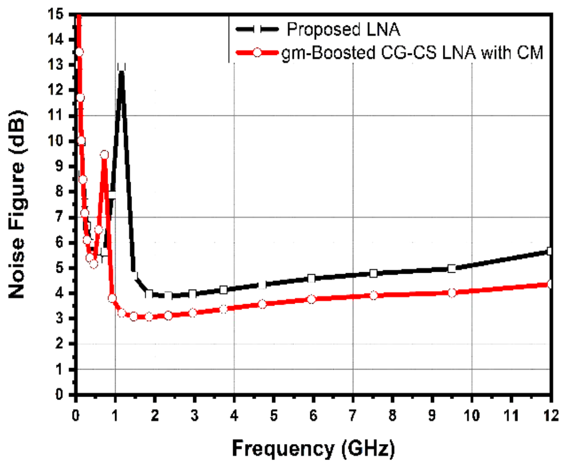


Fig. 15. Noise Figure (NF)

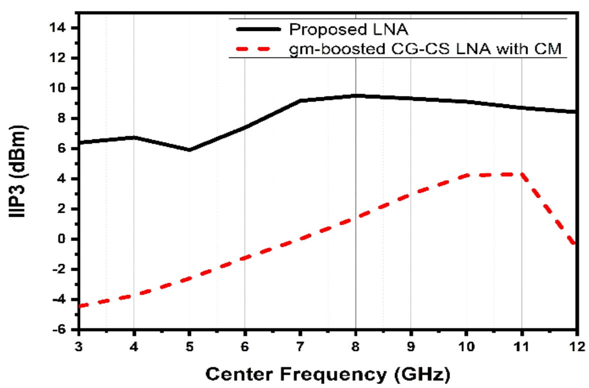


Fig. 16. IIP3 (dBm)

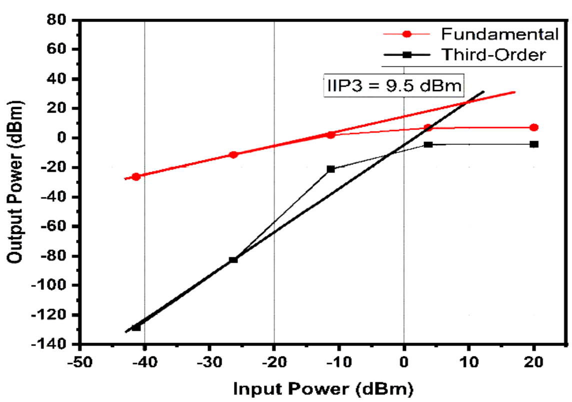


Fig. 17. IIP3 at 8 GHz

The noise of input CDS stage and g_m −boosting stage is cancelled at the output, when the noise cancellation condition indicated in Equation.10 is satisfied.NF of the suggested LNA is 3.9 dB to 5.29 dB in whole UWB, which slightly higher than the g_m-boosted CG-CS LNA as shown in Fig. 15. However, the degradation of NF for proposed circuit is 0.24 dB to 0.7 dB, making it an appropriate choice for wideband operation.

The suggested LNA exhibits a notable improvement in IIP3 due to the cancellation of 2nd order distortion at the g_m boosting and input stage as well as reduction in 2nd order interaction. IIP3 of suggested LNA, measured at different center frequencies with a 30 MHz frequency is 6.3 dBm to 8.8 dBm in whole UWB as shown in Fig. 16. . At the center frequency of 8 GHz, the maximum IIP3 of 9dBm is observed which is shown Fig. 17. To assess the IIP3 performance across various frequency intervals, IIP3 is evaluated at frequency spacings of 10MHz, 20MHz, and 30MHz, as illustrated in Fig. 18.As the frequency spacing increase, the IIP3 also exhibits a corresponding increase. The impact coupling capacitor C_A on IIP3 is also analyzed for various C_A values, and the results are depicted in Fig. 19. It is observed that as the value of C_A increases, the IIP3 at lower frequencies also rises, due to the decreased impedance provided by C_A. To verify the sensitivity of IIP3 on biasing voltages, bias of M_{1p} (V_p) is varies from 0 to 100mv. IIP3 is notably influenced by changes in the biasing voltage, with the highest IIP3 achieved at approximately 75 mV as shown in ***Fig***. *20.*

To further evaluate the robustness of the proposed LNA, simulations are performed under process, voltage, and temperature (PVT) variations. The key LNA performance parameters are summarized in Fig. 21. As depicted in Fig. 21(a), input matching (S11) is not well-matched for FS and SS process variations; however, for all other PVT variations, S11 remains below -10 dB. The gain (S21) shows minimal variation across PVT conditions, as illustrated in Fig. 21(b), while the noise figure remains below 6 dB, as shown in Fig. 21(c). Furthermore, to assess the robustness of IIP3 under PVT variations, simulations are conducted at 8 GHz, with measurements taken across different process corners. The results in Fig. 21(d) confirm that IIP3 remains above 0 dBm. **Table** 2. presents a comparison between the proposed work with derived simulation results from previously published wideband LNA [1], [3]–[5]. The figure of merits (FOM) [1] in Equation.25 is used to compare the performance of the suggested LNA. This FOM is well-suited for UWB LNAs as it effectively integrates critical performance factors such as bandwidth, gain, linearity, noise, and power efficiency. By placing bandwidth (BW) in the numerator, it directly accounts for wideband operation. The inclusion of IIP3 ensures linearity assessment, while (NF_min - 1) in the denominator appropriately penalizes excess noise. Additionally, P_{DC} reflects power efficiency, making the FOM ideal for low-power applications. Overall, this FOM serves as a comprehensive and practical metric for evaluating UWB LNAs, ensuring optimal functionality across the entire frequency range. Despite a modest decline in gain and noise performance, the suggested LNA achieves a high figure of merit when compared to others because of an increase in linearity.

$$FOM = 20\,log_{10}\left(\frac{BW[GHz]\cdot Gain[lin]\cdot IIP3[mW]}{P_{DC}[mW]\cdot(NF_{min}[lin]-1)}\right) \tag{25}$$

In comparison to [3] and [4], the proposed circuit utilizes fewer inductors to cover the entire ultrawideband, resulting in significant physical area savings. The results demonstrate that the proposed technique enhances the linearity across the entire ultra-wideband (UWB) spectrum.

5- Discussion

5-1- Limitations

The CDS configuration enhances linearity in the proposed circuit by introducing additional PMOS in the input and gm-boosting stages, increasing circuit's complexity and contributing to noise that degrades NF. However, it also degrades LNA gain when used for IIP3 improvement, creating a IIP3 trade-off with gain and NF, as depicted in Fig. 14 and 15. To establish an AC equivalent node, a capacitor (C_A) is added in CG-CDS, increase the circuit's physical footprint. Obtaining good IIP3 in CDS relies on optimal device biasing, where g_m' approaches to zero. But this biasing is sensitive to process and temperature variations, leading to IIP3 degradation.

6- Conclusion

This article introduces an innovative method to improve the linearity of a wideband g_m-boosted CG-CS LNA. The key idea behind this approach involves the integration of a Common Source (CS) complementary pair in the g_m-boosting stage and a complementary Common Gate (CG) pair in the input stage. Accurate biasing is applied to both complementary stages, effectively eliminating second-order distortion and second-order interaction leading to a substantial improvement in linearity. Additionally, a noise cancellation principle is implemented to cancel the noise generated by both the g_m-boosting and input stages. The proposed LNA, exhibits a remarkable enhancement in linearity across the entire Ultra-Wideband (UWB) range, specifically increasing from 6.3 dBm to 8.8 dBm, when compared to the g_m-boosted CG-CS LNA. This impressive improvement positions the proposed LNA as an excellent choice for applications involving multiple interference scenarios.

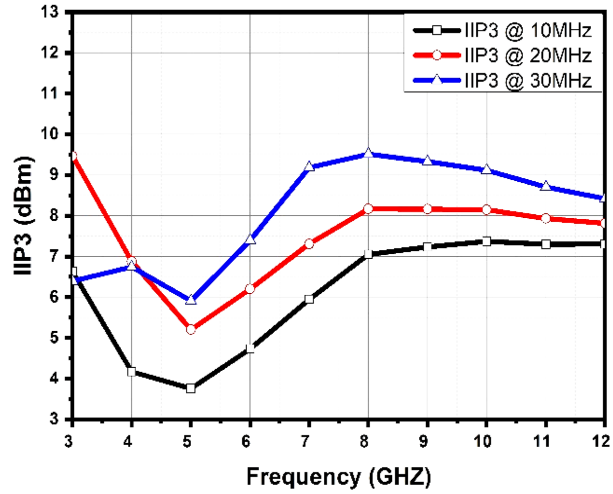


Fig. 18. IIP3 @ Frequency Spacing of 10 Mhz, 20Mhz, 30Mhz

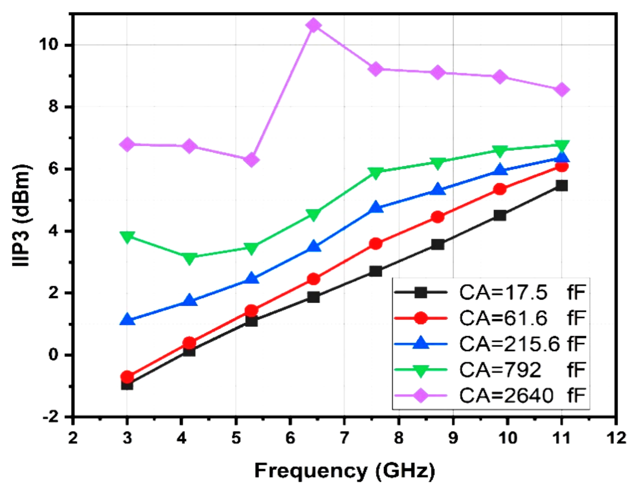


Fig. 19. IIP3 for different value of CA

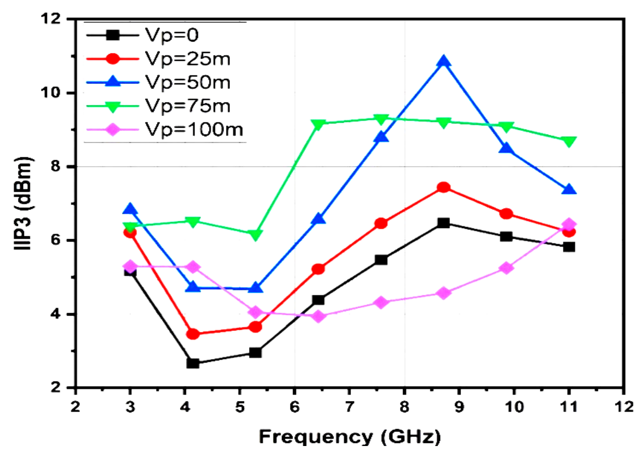


Fig. 20. IIP3 with variation in bias voltage V_p

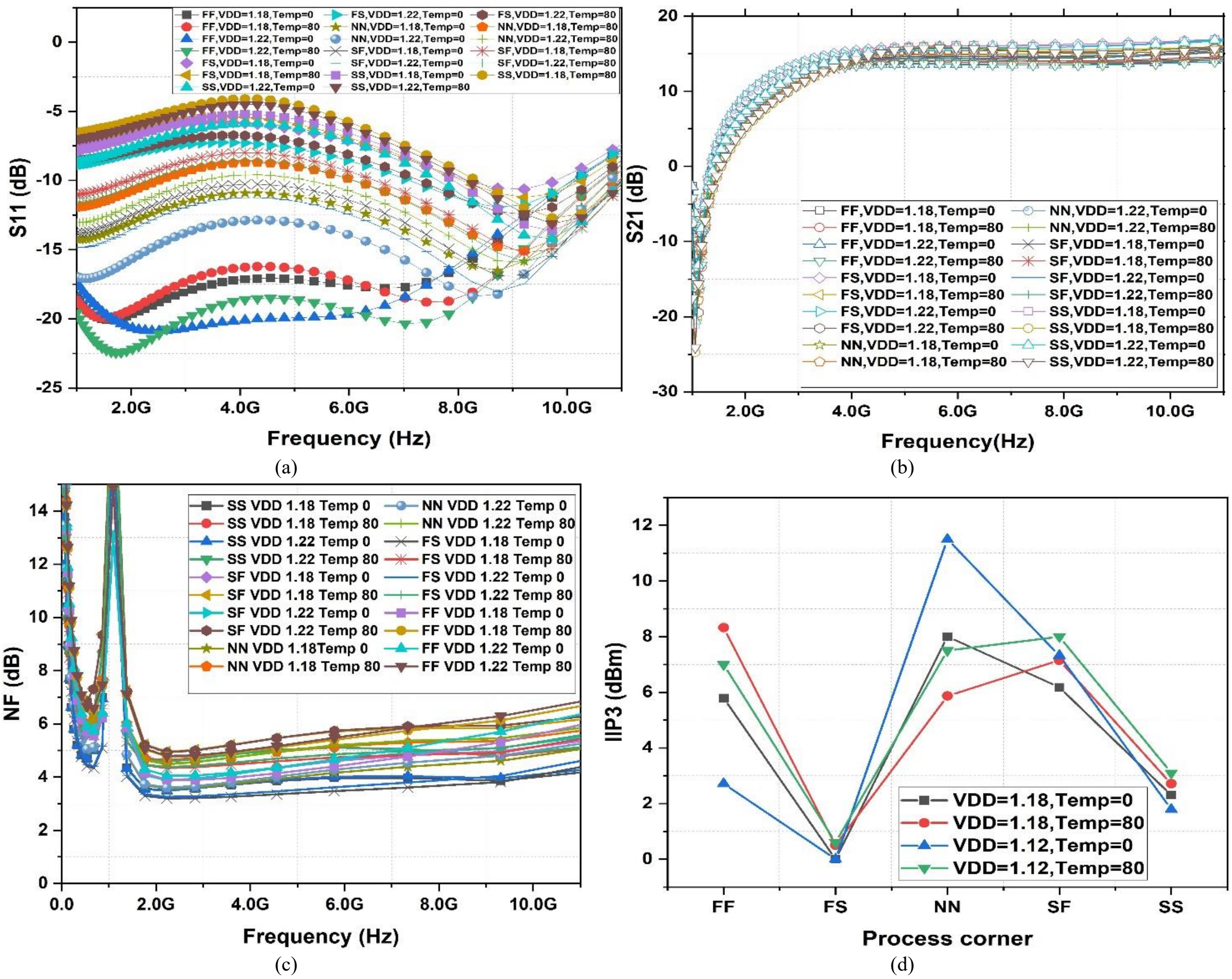


Fig. 21. PVT analysis of (a) S11 (dB) (b) Gain S_{21} (dB) (c)Noise Figure (d) IIP3

Table 2 Comparative Performance Evaluation of the Proposed Wideband LNA with Previously Reported LNAs

	S. Arshad [3]	**Q. Wan [4]**	**Z. Liu [1]**	**Z. Liu [5]**	**Proposed LNA**
CMOS Tech.	130nm	180nm	40nm	40nm	90 nm
Freq. Range (Ghz)	2.35-9.37	3.1-10.6	1-11	2-12	3.1 - 10.6
S11 (dB)	<-8*	<-10.6*	<-10*	<-10*	<-10
Gain(dB)	10.3*	15.8*	14-17*	16.5-19.5*	12.5-15.5
NF (dB)	3.68*	2.2-3.2*	3.5-5.5*	3.2-5.2*	3.9-5.26
IIP3(dBm)	-12.55*	-6*	-2.8 @ 6Ghz*	-3.5@ 6 Ghz*	9.5 @ 8 Ghz
Num. of Inductor	4	5	2	3	3
Power (mW)	9.97	9.0	9	9	11.36
Figure of Merit	-26.89	21.63	27.45	32.17	43.13

* Derived Simulation Results

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7- Future Work

Future directions, to enhance linearity through CDS techniques, include designing of robust CDS configurations that exhibit insensitivity to variations in process and temperature. Furthermore, the integration of digital control systems, advanced machine learning and AI algorithms with CDS can facilitate real-time optimization of CDS parameters which leads to better linearity.

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Journal of Information Systems and Telecommunication
Vol.13, No.2, April-June 2025, 91-110
http://jist.acecr.org
ISSN 2322-1437 / EISSN:2345-2773

Optimizing Hyperparameters for Customer Churn Prediction with PSO-Enhanced Composite Deep Learning Techniques

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Received: 24 Sep 2024/ Revised: 04 Apr 2025/ Accepted: 26 May 2025

Abstract
For Telecom operators, customer churn, i.e., the event when the customers leave a service provider, becomes a critical concern, studies have shown that acquiring new customers cost five times more than to retain them. In competitive markets, where is increasingly important, to sustain growth as well as profitability correctly predicting the tendencies for customer churn is important. Traditional predictive fashions frequently underperform due to the complex nature of client behavior. In this examine, we introduce a unique composite deep mastering framework whose hyperparameters are optimized the usage of the Particle Swarm Optimization (PSO) set of rules. Our method integrates a couple of neural community architectures to effectively capture each spatial and temporal patterns in client interactions. The PSO set of rules systematically first-rate-tunes parameters including activation functions, regularization techniques, gaining knowledge of rates, optimizers, and neuron counts—ensuing in a model that demonstrates robust overall performance. We evaluated our approach the usage of key metrics consisting of accuracy, precision, recollect, F1 score, and ROC AUC on a numerous purchaser dataset. Comparative analyses were conducted in opposition to established deep studying fashions (LSRM_GRU, LSTM, GRU, CNN_LSTM) in addition to other conventional methods (KNN, XG_BOOST, DEEP BP-ANN, BiLSTM-CNN, and Decision Tree). Experimental results stompy that our PSO-enhanced composite deep learning model stands out significantly compared with conventional models. Comparing the ROC-AUC scores of 0.932 and 0.93, F1 scores of 0.90 and 0.895, and accuracy rates of 83.2% and 93% on both Cell2Cell and IBM Telco datasets. it is indeed effective for practical churn prediction use incitements efficiencies. Var The experimental results demonstrate that our PSO express tree model outperforms conventional methods, achieving better performance with ROC totter score above 0.932 and 0.93, F 1 scores above 0.90 and 0.895 as well as accuracy rates in excess of 83.2% (% paper) and 93% (on the Telco data set) for Cell2Cell and IBM Telco respectively. This is further confirmation of its effectiveness and promise for practical churn prediction applications.

Keywords: Customer Churn Prediction; Hyperparameter Optimization; Particle Swarm Optimization (PSO); Deep Learning Models; Telecommunications Analytics.

1- Introduction

The fast upward thrust of e-commerce platforms has transformed client engagement and retention techniques. In a aggressive panorama, predicting client churn is vital for commercial enterprise increase and profitability [1]. Although considerable studies have evolved various churn prediction fashions, the dynamic nature of purchaser conduct and records complexity, mainly in telecom with its substantial and diffused interaction information, pose ongoing challenges. Advances in system mastering (ML) and deep gaining knowledge of (DL) provide promising answers, yet their effectiveness relies upon on precise hyperparameter tuning—a complicated mission because of high-dimensional seek spaces and computational costs[2] [3].
Despite the widespread use of ML and DL in the prediction of pimple, there is a remarkable difference in adapting hyperparameters to promote accuracy and efficiency. Traditional methods such as web searches and random discovery are computational and often sub -form [4]. General DL technology, which utilizes diverse nervous network strength, and complicates further setting.

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This study addresses this gap by suggesting a bio-induced algorithm, particle crew optimization (PSO) to adapt to hyperparameters in a composite DL model for telecommunications spread [5].

This research goals to broaden and validate a powerful approach for optimizing hyperparameters in composite deep mastering fashions for telecom churn prediction. It pursues 3 targets:

- Create a PSO-embedded composite DL framework integrating Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and Gated Recurrent Units (GRUs) to capture nuanced client behavior and transaction styles, superior by way of a novel integration of PSO with dropout regularization and mini-batch schooling for robustness and efficiency.
- Apply Particle Swarm Optimization (PSO) to song hyperparameters, enhancing churn prediction accuracy and computational performance over conventional techniques like random seek and grid search.
- Evaluate the PSO-enhanced version's overall performance in opposition to conventional models (LSRM_GRU, LSTM, GRU, CNN_LSTM) the usage of metrics along with accuracy, precision, consider, F1 rating, and ROC AUC.

The difference identified by achieving these goals will be addressed, a new approach will be offered to improve the grinding prediction model and telecommunications companies will be given action - provoking insights to improve retention strategies. This research contributes significantly to the future analysis and telecommunications spread:

- Novel PSO integration: We suggest a creative method that uses PSO for fine-tuning hyperparameters in the general DL model, improves the efficiency and performance of traditional techniques, as validation is valid.
- This study makes widespread comparisons with models such as LSTM, GRU and CNN_, and perform better performance in accuracy, precision, recall, F1 points and ROC AUC, which promotes BI-inspired hyperparameters.
- Practical framework: It provides a scalable, adaptable PSO-DL model for telecom and improves the prediction in different data sets.
- And analysis goals: It shows PSO's ability to adapt to DL models, and encourages the further discovery of the evolutionary algorithm in large data and complex predictions.

The paper proceeds as follows: Section 2 opinions existing work on churn prediction and optimization strategies. Section 3 describes the PSO algorithm and its integration into our model. Section four outlines the proposed technique, which include information training and version improvement. Section five offers the experimental results, observed by a discussion in Section 6 and conclusions in Section 7.

2- Related Work

Understanding and predicting customer churn has been a focal point of research across various sectors, particularly the telecom industry, where the possibility of accurately predicting churn has far reaching implications in terms of business revenue and growth. Historically, churn prediction models primarily rested on statistical and machine learning methods, such as logistic regression, decision trees, and support vector machines (SVMs)[6]. Although effective to a degree, these methods often lacked the ability to identify complex and non-linear patterns hidden within the large volumes of customer interactions and behaviors. The ever-increasing complexity of these patterns has forced the exploration of more sophisticated analytical techniques that are capable of accurately identifying and predicting customer churn [7].

It has been proved that recent progress in deep learning yields productive ways for improving churn prediction models. Deep learning is powerful because it is able to learn hierarchical data representations and, consequently, it has been shown to noticeably outperform traditional machine learning models in identifying complex patterns in large datasets[8]. Various deep learning architectures, e.g., Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs) and their flavors like Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs) have been tentatively applied to churn prediction and these models, have displayed state-of-the-art performance on myriad sequential and time-series data – making them tailor-made for analyzing customer interaction sequences, and transaction histories [9].

The performance of deep learning models depends heavily on the choice of hyperparameters. Manually tuning these parameters is an impossibly time-consuming process, which is why automated hyperparameter optimization techniques like Grid Search, Random Search, Bayesian Optimization, and Evolutionary algorithms such as Genetic Algorithms (GAs) and Particle Swarm Optimization (PSO) have become extremely popular. Of these, PSO, a bio-inspired optimization algorithm, has shown promise in navigating the hyperparameter search space efficiently [10]. The objective of optimizing a given objective function with respect to a model's hyperparameters is universal in the field of machine learning. This objective is commonly addressed using grid, random or other more computational expensive techniques. Particle Swarm Optimization (PSO) provides a heuristically driven solution to this problem, simulating the social behaviors of bird flocking or fish schooling. Applications for this recently have been numerous within various domains. However, PSO application to optimizing hyperparameters for deep learning-based churn prediction models is underexplored[11].The individual components of churn prediction, deep learning and hyperparameter optimization have been thoroughly investigated in the literature. However, there is a dearth of studies within the research literature that investigate the integrated application of PSO to tune composite deep learning models in churn prediction. This present void in the research literature presents an enticing prospect of making substantial contributions to this field of research. We are proposing a novel hybridization of PSO algorithm against a deep learning neural network architecture to attempt to simultaneously address the problems of churn prediction that have surpassed the capabilities of current practices.

We discuss five key innovations in the evolving landscape of churn prediction using the Deep Learning (DL) and Machine Learning (ML)[12], [13]: the rise of DL, the creation of embedded space using DNN, the advent of TL and Ensemble-based Meta-Classification, proposed in "TL-DeepE", Associative Chaos Networks, a radically new DNN architecture, that was introduced in, Jazz Networks, which presented Chaos and Laws through the lens of music, Cloud Machine Learning in Healthcare by Adam Gasiewski and Mark W. Hester and Epsilon Computing's ETL as a Service. This method achieved high accuracy on telecom datasets — underscoring the synergies between TL and ensemble methods in churn prediction — by fusing fine-tuned DCNNs with ensemble methods.

Subsequent to its successful use of DCNN in modeling data at successive levels of abstraction, follow-up work saw such an architecture (ANN) outperform traditional models on the IBM Telco Churn dataset, thus demonstrating that artificial neural networks such as these, which feature self-learning capabilities, are able to readily outperform conventional algorithms by automatically and efficiently learning from big data [7].

In addition to these studies, a study used a novel model to evaluate the performance of a Customer Churn Prediction (CCP) model with a Naïve Bayes classifier shedding light on the performance of different sample sets, suggesting feature selection methods as an area for future work. Another study applied a Deep Learning method to a Telco dataset, yielding high-accuracy churn prediction by analyzing customer attributes, underscoring DL as a useful tool for identifying the key churn predictors. Finally, exhaustive analyses with various ML algorithms have arrived at the optimal churn prediction classifiers, chief among them being Logistic Regression. The collective work they did here is important as this not only advances our understanding of churn prediction mechanisms, it also opens new doors for the application of DL and ML to provide deep insights and drive actions in customer retention strategies.

The study [3], is a detailed description of how to forecast customer churn, a critical area for telecoms that are looking to keep and grow their subscriber base. From a study that "introduces a comprehensive approach for churn prediction in the telecommunications industry based on Deep Learning (DL) and Machine Learning (ML) with independent evaluations of both the activation functions and two feature selection methods," the paper details how the authors developed a predictive model using Deep Backpropagation Artificial Neural Networks (Deep-BP-ANN) integrating it with two different feature selection methods:

Various techniques employed in this research include Variance Thresholding and Lasso Regression and this model is further refined with the use of an early stopping technique that prevents overfitting, which is a common problem with Machine Learning models. The authors employ dropout and activity regularization to minimize overfitting. The performance of the model is evaluated using both holdout and 10-fold cross-validation evaluation methods. Random Oversampling is also used to balance the dataset, since in real world customer churn datasets, there are comparatively much smaller number of churners. The results show that Deep-BP-ANN model perform better and the combination of lasso regression for feature selection and activity regularization perform exceedingly well in predicating customer churn, outperforming traditional Machine Learning (ML) techniques like XG_Boost, Logistic Regression, Naïve Bayes, and KNN. This performance is consistent across two real-world telecom datasets: IBM Telco and Cell2Cell.

The paper [3] points out that the Deep-BP-ANN model improved churn prediction accuracy by over 17%, against other deep learning models and over 22%, against other ML techniques on the same datasets. The use of lasso regression for feature selection, and early stopping, to find the optimal number of the epochs were central to why the model works so well. The findings suggest that deep learning may be a highly inclusive and therefore, low-cost method due to cheaper filtered data, to process complected feature relationships in complex, large scale", churn prediction works. The study also identifies some caveats, including the use of datasets created for the purpose (DS and IC) that". may not capture many established challenges of the telecom industry".

The study [4] looks at the modern organizations, where customer tend to switch over to competitors due to poor service quality and satisfaction. It introduces a novel deep learning model, BiLSTM-CNN, that predicts customer churn with far greater accuracy than the more traditional machine learning models. The abstract sets the stage for the research by pointing out that existing ML/DL algorithms have many limitations when it comes to customer churn prediction, as they fail to forecast accurately. By integrating Bidirectional Long Short-Term Memory (BiLSTM) and Convolutional Neural Networks (CNN), the model aims to effectively capture and analyze the customer data to foresee churn at an accuracy of 81%, as demonstrated in a benchmark dataset.

The paper shows that the proposed BiLSTM-CNN outperforms several traditional machines learning classifiers such as Support Vector Machines, Decision

Trees, K-Nearest Neighbors in predicting customer churn [4]. This advantage comes from its ability to take into account sequential data in both ways, and then capturing patterns of customer behavior more extensively. The paper then evaluates the precision, recall and F1 scores of the model, and compares them in detail with similar metrics of existing machine learning models as even well as deep learning models. Finally, the paper underscores the model's effectiveness in increasing the accuracy of churn prediction, which can be critical for telecom companies in deploying ad-hoc customer retention strategies. The paper also lists a number of limitations - some of which suggest avenues for future work, like the focus on binary classification and reliance only on numerical features, which could be the target of multi-dimensional CNN approaches; others touch upon broader possibilities, such as the use of multiclass classification to reduce feature zipping, and incorporation of a wider range of features for more precise predictions.

The paper [5] examines the very important problem of customer churn within the telecommunications sector, and the development of a predictive model that utilizes both parsing and clustering techniques. This model comes into being with the hopes of identifying customers likely to churn and why, in a telecom industry with vast amounts of data that is produced daily. Using a feature selection process with information gain and correlation attribute evaluation filters, our approach is able to successfully classify customer data using random forest, with 88.63% accuracy for correctly classified instances. In the next step, we performed a post processing approach on the churned customers by using Cosine Similarity to segment them into clusters that would help in retention owed to specific behavior and preference of the customers.

This approach has proven help to achieve a high accuracy in churn prediction while being able to help customer carriers to distinguish which customers are most likely to leave their network provider. The identification of causes of churn coming from low-level application data has the possibility to practical afford operators to direct their marketing campaigns as well as subscriber offerings for this activation. This would lead mobile carriers develop marketing and retention campaigns which are specifically designed for its subscribers, while being able to make quite sure. Instead of using the information which one thinks will attract those who are most likely to leave. The study acknowledges some limitations, including the model's dependency on particular datasets, and propose several research directions for enhancing the model's applicability to diverse datasets, as well as the integration of further predictive techniques. This paper is based on work that has been funded by a variety of research funding. The extensive teamwork behind this research has played a key role in the advancement of churn prediction methodologies in the telecom sector.

The study [14] assesses the importance of hyperparameter tuning in improving the performance of deep learning models used for predicting customer churn in the telecommunications sector. The abstract suggests that the focus of the paper will be on comparing multiple machine learning techniques while giving "special attention on deep learning" for the purpose of predicting churn of customers. Furthermore, it states that there are very few empirical studies that show how hyperparameters influence the model's performance. The authors experiment with the different configuration including: type of optimizers, activation functions and batch sizes and argue that using ReLU in the hidden layer and the sigmoid function in the output layer provides the best accuracies of the model in predicting churn.

Unsurprisingly, the results show that the model’s performance is considerably greater when the ReLU activation function in hidden layers is used in conjunction with the sigmoid function in the output layer. Due to this configuration the model has an accuracy of close to 86.9%. It was also noted that using smaller batch sizes can actually be better for the overall performance of the model with a noticeable drop in its performance as the batch sizes approached the size of the test dataset. A deeper look at the different optimizers also found that the RMSProp optimizer outperformed the others over the 500 epochs proving its ability to reduce the loss function and increase the predictive accuracy of the model. This led the conclusion that the hyperparameter tuning is a critical component of any deep learning models for churn prediction and that the right combination of activation functions, batch sizes and optimizers could greatly increase performance. This study is important as it advances both the theoretical and practical understanding of churn prediction within the telecommunications sector and will serve as a guide for researchers to continue to improve deep learning models for this application [14].

The study [15] focuses on enhancing patron retention techniques inside the telecommunication industry with the aid of predicting patron churn the usage of machine studying strategies. The observe proposes using a Multilayer Perceptron (MLP) neural network and compares its performance with traditional statistical techniques together with Multiple Regression Analysis and Logistic Regression Analysis. The effects indicate that the neural network achieves a advanced accuracy of 91.28% in predicting consumer churn, significantly outperforming the regression-based totally models. This shows that system mastering models, mainly neural networks, provide a extra powerful technique to churn prediction and may be used to decorate patron retention efforts.

The paper's key contributions include the application of a synthetic neural community to the client churn trouble, demonstrating its blessings over conventional statistical strategies. The research methodology includes records extraction, preprocessing, and the software of MLP neural networks, with overall performance measured based totally on accuracy, sensitivity, and specificity. A fundamental hindrance of the take a look at is the reliance on a limited dataset from a unmarried telecommunication issuer, which may affect generalizability. Nevertheless, the findings fortify the effectiveness of neural networks in predictive analytics, imparting a precious opportunity to traditional statistical techniques for improving client retention techniques in competitive markets.

The research paper [16] addresses customer churn, a major concern for telecom companies. It proposes a predictive model to identify customers likely to leave using machine learning techniques. The study applies the enhanced Relief-F feature selection algorithm to refine the dataset and employs Random Forest and Convolutional Neural Networks (CNN) for classification. Results show CNN achieving a 94% prediction accuracy, outperforming Random Forest at 91%. The study highlights the importance of feature selection in improving prediction accuracy and suggests that CNN is the superior model for churn prediction in telecom.

The methodology leverages statistics mining and device getting to know, especially Relief-F for characteristic choice, accompanied via category the use of Random Forest and CNN. The look at makes use of a dataset of three,333 telecom clients, selecting 14 key functions for analysis. The research demonstrates that CNN's deep getting to know method affords extra particular churn predictions than traditional system mastering models. However, the observe acknowledges obstacles, such as the need for in addition optimization and exploration of other gadget getting to know fashions. The conclusion emphasizes that telecom corporations can notably enhance client retention strategies by way of adopting superior AI strategies like CNN, ensuring greater powerful churn prediction and commercial enterprise growth.

The paper [17] explores the position of machine getting to know in predicting patron churn and enhancing retention techniques inside the telecom industry. It discusses conventional churn prediction challenges, inclusive of information fine troubles and confined version effectiveness, and highlights the benefits of gadget mastering strategies like selection trees, guide vector machines, and ensemble techniques. The paper emphasizes how device getting to know allows actual-time statistics analysis, improves scalability, and enhances predictive accuracy. It additionally identifies ethical issues related to data privateness and the want for interpretable AI fashions. The research suggests that integrating AI-pushed predictive analytics can extensively reduce churn, optimize retention strategies, and enhance telecom commercial enterprise overall performance. The study contributes by analyzing gadget gaining knowledge of fashions against traditional statistical techniques, proving the superiority of AI-based totally processes for churn prediction. Its technique includes reviewing existing literature, comparing exclusive gadget learning algorithms, and discussing demanding situations such as overfitting, model selection, and implementation charges. The paper recognizes obstacles, which include records integration problems and the want for interpretable AI solutions. The findings recommend that actual-time prediction, personalized retention techniques, and AI-pushed customer support automation will shape the destiny of telecom purchaser management. The conclusion underscores the importance of machine getting to know in reducing churn and improving purchaser loyalty, making AI-driven retention techniques essential for telecom companies' long-term success.

The study [18] explores the task of purchaser churn within the telecommunications area and the effectiveness of gadget studying fashions in predicting it. The observe evaluates diverse classifiers, which includes Random Forest, XGBoost, LGBM, Logistic Regression, Decision Trees, and an Artificial Neural Network (ANN). It employs characteristic selection, hyperparameter tuning, and ensemble averaging to optimize overall performance. The results display that the LGBM and XGBoost fashions outperform others, with the best accuracy of eighty.36%. The research highlights the significance of gadget studying in enhancing consumer retention charges and operational performance in telecom groups. This look at contributes via evaluating multiple machines getting to know models and showcasing the advantages of ensemble methods in churn prediction. It follows a structured technique, which includes information preprocessing, exploratory data analysis, model education, and assessment the use of cross-validation strategies. The number one hassle of the take a look at is its reliance on a publicly available dataset as opposed to real-world telecom statistics, which may affect generalizability. The findings recommend that machine getting to know fashions, particularly ensemble procedures, provide more accurate churn predictions than conventional techniques. The conclusion emphasizes the need for telecom groups to adopt superior predictive analytics and suggests destiny research into integrating blockchain-based totally solutions for secure consumer statistics management.

Table 1: Comparison of algorithms

Category	Abstract	Contributions	Methods Used	Results	Conclusions	Limitations
"Customer Churn Prediction in Telecommunication Industry Using Deep Learning" [3]	Explores Deep Backpropagation ANN with feature selection for churn prediction.	Demonstrates DL models' efficacy in churn prediction with optimized feature selection.	Deep-BP-ANN, Variance Thresholding, Lasso Regression.	Achieved high accuracy on telecom datasets, outperforming traditional ML methods.	Validates the potential of DL for churn prediction with appropriate feature selection.	Limited by specific datasets; may not generalize across the telecom sector.
"Customer Churn Prediction Using Composite Deep Learning Technique" [4]	Introduces a novel BiLSTM-CNN model to enhance churn prediction accuracy.	Shows BiLSTM-CNN model's superior accuracy over traditional ML methods.	BiLSTM-CNN.	Reached 81% accuracy, surpassing conventional classifiers.	Confirms the BiLSTM-CNN model as an effective tool for telecom churn prediction.	Focused on binary classification and numerical features only.
"A Churn Prediction Model using Random Forest: Analysis of ML Techniques for Churn Prediction" [5]	Develops a churn prediction model combining classification and clustering via Random Forest.	Highlights the effectiveness of integrating classification and clustering for detailed churn analysis.	Random Forest, information gain, correlation attribute ranking.	Random Forest model showed high accuracy and provided insights into churn reasons.	Proves the utility of combining methods for a nuanced understanding of churn.	Model's dependence on specific datasets could limit broader applicability.
"Impact of Hyperparameters on Deep Learning Model for Customer Churn Prediction in Telecommunication Sector" [14]	Investigates the impact of hyperparameter tuning on deep learning model performance for churn prediction.	Emphasizes the significant role of hyperparameter tuning in improving model performance.	Activation functions, batch sizes, optimizers in DL models.	Found optimal combinations of activation functions and optimizers that significantly improved accuracy.	Highlights the critical impact of hyperparameter tuning on churn prediction models.	Study's reliance on a synthetic dataset may not fully represent real-world complexities.
A Multi-Layer Perceptron Approach for Customer Churn Prediction[15]	The look at explores the software of a Multilayer Perceptron (MLP) neural network to expect consumer churn in the telecommunication zone, comparing it with conventional statistical models like Multiple and Logistic Regression.	Introduces MLP as a superior predictive device for consumer churn, demonstrating its higher accuracy (91.28%) as compared to statistical procedures. Provides insights into how telecom providers can proactively maintain customers.	Data series from a Malaysian telecom employer, preprocessing, function extraction, and evaluation using MLP neural network and statistical fashions (Multiple Regression and Logistic Regression).	MLP neural community carried out the highest accuracy (91.28%) in predicting patron churn, outperforming Multiple Regression (78. 84%) and Logistic Regression (75.19%).	The study confirms the superiority of the nervous network on the traditional statistical model to predict the customer's brainstorming, and exposes their ability to increase customers' storage strategies.	Requires excessive computational power, capability overfitting of the version, and the need for non-stop updates with new purchaser statistics for foremost
A Churn Prediction System for Telecommunication Company Using Random Forest and Convolution Neural Network Algorithms [16]	The take a look at proposes a churn prediction version for telecom agencies the use of Random Forest and Convolutional Neural Network (CNN) classifiers. It objectives to enhance predictive accuracy by leveraging an stepped forward Relief-F function choice algorithm.	The quarter introduces a hybrid approach by combining random forest and CNN for prediction. Traditional methods show the effectiveness of deep learning in telecommunications analysis with better performance from traditional methods.	Data collection from a telecom dataset, characteristic extraction the usage of the Relief-F set of rules, and class the usage of Random Forest and CNN fashions.	CNN performed a better prediction accuracy (٩٤%) as compared to Random Forest ٩١%), demonstrating the capability of deep getting to know in churn prediction.	The study exposes CNN as a better method of predicting customer driving, and strengthens the need for advanced machine learning techniques in telecom analysis.	Computationally extensive fashions, requirement for large datasets, and demanding situations in actual-time implementation due to processing constraints.
implementing machine learning techniques for customer retention and churn prediction in telecommunications [17]	The paper explores the application of machine getting to know techniques in predicting patron churn and enhancing retention in telecommunications. It evaluates diverse gadget learning fashions, discusses data-related demanding situations,	Highlights the advantages of machine learning over traditional churn prediction methods. The author presents three potential improvements which include real-time analytics together with explainable AI systems and	Analysis of decision bushes, guide vector machines, ensemble gaining knowledge of, and deep studying fashions. Comparison of system gaining knowledge of techniques with conventional statistical	The performance of random forests and gradients as a dress algorithm surpasses traditional methods in identifying thought-to-be ill-formed notions. The teaching methods that deliver intensive instruction led to additional learning gains	Machine gaining knowledge of presents superior scalability, accuracy, and real-time processing for churn prediction. The have a look at emphasizes integrating AI-pushed retention techniques for telecom companies	Challenges in information availability and excellent, computational necessities, interpretability of deep mastering fashions, and moral issues in managing purchaser statistics.

Category	Abstract	Contributions	Methods Used	Results	Conclusions	Limitations
	and shows innovations for improving predictive accuracy.	customized retention approaches.	techniques for churn prediction.	although they do not explain concepts.	to decorate patron loyalty.	
Customer Churn Prediction for Telecommunication Companies using Machine Learning and Ensemble Methods[18]	The study checks the customer who throws himself in the telecom sector using the machine learning classification, including Random Forest, XGBOST, LGBM, Logistic Region and Decision Tree. The study forecasts use learning to improve accuracy and customers' storage strategies.	Introduces an optimized ensemble model for churn prediction, highlighting the effectiveness of Random Forest, XGBoost, and LGBM. Provides a comparative evaluation of multiple classifiers and hyperparameter tuning techniques.	Utilizes a telecom churn dataset, preprocessing strategies, and device studying classifiers (Random Forest, XGBoost, LGBM, Logistic Regression, Decision Trees, and ANN). Hyperparameter tuning and ensemble averaging had been applied for optimization.	LGBM and XGBoost done the best accuracy (80%) amongst examined models. The ANN model reached 79% accuracy, barely lower than the ensemble strategies. The take a look at confirms the effectiveness of ensemble learning in churn prediction	Machine learning models, specifically ensemble strategies, offer advanced predictive performance for telecom churn prediction. Optimized fashions can beautify consumer retention techniques for telecom corporations.	A specific dataset, which limits questions of potential generality, calculation complexity of the artists' methods and limited to challenges in implementing real - time.

3- Background and Explanation

Particle Swarm Optimization (PSO)[19] is a computational method that optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality. PSO simulates the social behavior of birds within a flock or fish within a school. Originally introduced by Kennedy and Eberhart in 1995, PSO is inspired by the social behavior patterns of organisms that move in groups. Unlike evolutionary algorithms, PSO is guided not only by the best solution (or position) found by the swarm but also by the best solution found by each individual particle.

PSO operates by initializing a group of random particles (solutions) and then searching for optima by updating generations. In every iteration, each particle updates its velocity and position based on two "best" values[20]:

- Pbest (Personal Best): The best solution (position) it has achieved so far. This value is updated if the current position is better than Pbest.
- Gbest (Global Best): The best solution found by any particle in the population. This value is shared and updated across all particles in the swarm.

The PSO formula to update the velocity and position of particles can be broken down into the following[21]:

- Velocity Update: The velocity of each particle is recalculated based on its Pbest and Gbest. The velocity update is influenced by cognitive and social components, where the cognitive component reflects a particle's own experience and the social component is the learning from the swarm.
- Position Update: The position is then updated based on the new velocity. This has the effect of each particle moving toward its Pbest and Gbest locations in every dimension of the search space.

PSO in Hyperparameter Optimization: When it comes to optimizing hyperparameters for deep learning models, PSO can be employed to traverse the hyperparameter space automatically and efficiently. Each particle represents a potential set of hyperparameters. The fitness of each particle is determined based on the performance of the deep learning model (e.g., accuracy, F1 score) trained with these hyperparameters. The swarm iterates and converges upon the best solution — the set of hyperparameters that enhances the model's performance. The strength of PSO lies in its simplicity, ease of implementation, and the fact that it can quickly converge to a good solution in complex and high-dimensional optimization problems without requiring gradient information, which makes it particularly ideal for complex and high-dimensional optimization problems such as hyperparameter tuning for deep learning models.

Significance in Churn Prediction: The application of PSO to optimize hyperparameters in composite deep learning techniques for churn prediction presents a groundbreaking utilization of swarm intelligence that enhances the accuracy and efficiency of the model, and offers a powerful means of addressing the time-consuming and often impractical manual hyperparameter tuning that faces the intractably vast search space involved in advancing the capabilities of predictive analytics in the arena of customer churn management.

Pseudocode for Particle Swarm Optimization (PSO)
1. Initialize the swarm of particles with random positions and velocities in the D-dimensional problem space. 2. For each particle, evaluate the fitness of its current position.

3. Set Pbest to the initial position of each particle.
4. Identify the particle with the best fitness and set Gbest to this particle's position.
5. While the termination criterion is not met (e.g., maximum number of iterations or a satisfactory fitness level):
   a. For each particle i in the swarm:
      i. Update the velocity based on Pbest and Gbest using the formula:
         V[i][d] = w * V[i][d] + c1 * rand() * (Pbest[i][d] - X[i][d]) + c2 * Rand() * (Gbest[d] - X[i][d])
         Where:
         - V[i][d] is the velocity of particle i in dimension d.
         - X[i][d] is the current position of particle i in dimension d.
         - Pbest[i][d] is the best known position of particle i in dimension d.
         - Gbest[d] is the best known position among all particles in dimension d.
         - w is the inertia weight.
         - c1 and c2 are cognitive and social parameters, respectively.
         - rand() and Rand() are random functions in the range [0,1].
      ii. Update the position of the particle using the formula:
         X[i][d] = X[i][d] + V[i][d]
      iii. Evaluate the fitness of the new position.
      iv. If the fitness of the new position is better than the fitness of Pbest[i], update Pbest[i] to the new position.
   b. Identify the particle with the best fitness among all Pbest positions and update Gbest if necessary.
6. Return Gbest as the best solution found.

Velocity Update Formula[20], [21]:

$$\mathrm{V}_{\mathrm{i,d}}^{(\mathrm{t+1})} = \mathrm{w} \cdot \mathrm{V}_{\mathrm{i,d}}^{(\mathrm{t})} + \mathrm{c}_1 \cdot \mathrm{rand}(\,) \cdot \left(\text{Pbest}_{\,\mathrm{i,d}} - \mathrm{X}_{\mathrm{i,d}}^{(\mathrm{t})} \right) + \mathrm{c}_2 \cdot \mathrm{Rand}(\,) \cdot \left(\text{Gbest}_{\,\mathrm{d}} - \mathrm{X}_{\mathrm{i,d}}^{(\mathrm{t})} \right) \quad (1)$$

Position Update Formula[20], [21]:

$$\mathrm{X}_{\mathrm{i,d}}^{(\mathrm{t+1})} = \mathrm{X}_{\mathrm{i,d}}^{(\mathrm{t})} + \mathrm{V}_{\mathrm{i,d}}^{(\mathrm{t+1})} \quad (2)$$

Where:

- $V_{i,d}^{(t)}$ is the velocity of particle i in dimension d at time t.
- $X_{i,d}^{(t)}$ is the position of particle i in dimension d at time t.
- Pbest $_{i,d}$ and Gbest $_{d}$ are the best personal and global positions encountered so far.
- w is the inertia weight that controls the impact of the previous velocity on the current velocity.
- c_1 and c_2 are acceleration coefficients that control the personal and social contribution to the velocity update.

rand () and Rand () are two random functions generating numbers between 0 and 1, providing stochastic elements to the search.

4- Proposed Model

We introduce the model we have developed to predict Customer Churn. The model has four main stages as displayed in Figure 1. First, we introduce the model and talk through its data flow. We're building a model to predict customer churn; our improved model will take advantage of advanced deep learning techniques to capture intricate patterns in telecom customer data. We know that developing and implementing a model to predict churn is a meticulous process from data prep to model development and testing. Typically, the first step of such a process is to import necessary libraries for data handling, preprocessing, and model building. After that, a dataset is imported; in this project, we read our dataset, which was stored in a CSV file, and performed Exploratory Data Analysis (EDA) which entails educating oneself about the characteristics of the dataset, identifying any missing values, outliers, or obvious patterns in the data, in an attempt to help the reader to better understand the dataset we are working with as a model is developed. This process is necessary because it allows us to understand the structure of the dataset and subsequently prepare it for the heavy lifting of the model building. We present the general process and flow of the system, including why it's needed and where the model fits in as a production system.

The next step involves using a more advanced pipeline for data preprocessing that leverages StandardScaler for normalizing the numerical features, and OneHotEncoder for encoding categorical features. This is extremely important in making the data compatible with the neural network model, and in ensuring all features have the same scale. Following that, the innovative neural network architecture is discussed. It is based on a combination of Convolutional Neural Networks (CNN) followed by a few Gated Recurrent Units (GRU) and Long Short-Term Memory (LSTM) layers, which allows it to learn both spatial and temporal patterns in the data. To optimize this architecture further, we made use of a function that uses evolutionary algorithms — specifically Particle Swarm Optimization (PSO) — for hyperparameter tuning that was wrapped within a scikit-learn Pipeline, making it as easy to use as the ones provided by the library itself. This function carefully evolves the model to identify a set of hyperparameters that provide the best predictive performance we could achieve in this task. Model evaluation is done in terms of accuracy, precision, recall, F1 score, and ROC AUC score. We show the model was able to achieve par performance in the training set, and very close to that in the testing set as well. The results are analyzed in depth and visualized. This workflow provides a strong demonstration of how deep learning and evolutionary algorithms can be combined for the nuanced task of customer churn prediction, and provides significant contributions to both the field and to telecom companies who are looking to enhance their customer retention strategy.

This proposed approach, unique in the rigor of its methodology and in the elegant application of deep learning techniques combined with evolutionary algorithms, aims to set a new state-of-the-art in the context of churn prediction. It demonstrates a profound appreciation for the complexity in customer data and illustrates the ability of our model to navigate this complexity to make accurate churn predictions. As such, this research contribution provides not only a novel framework for the academic community, but also a useful model for practitioners in the domain of telecommunications who may wish to employ this model in a "real world" scenario.

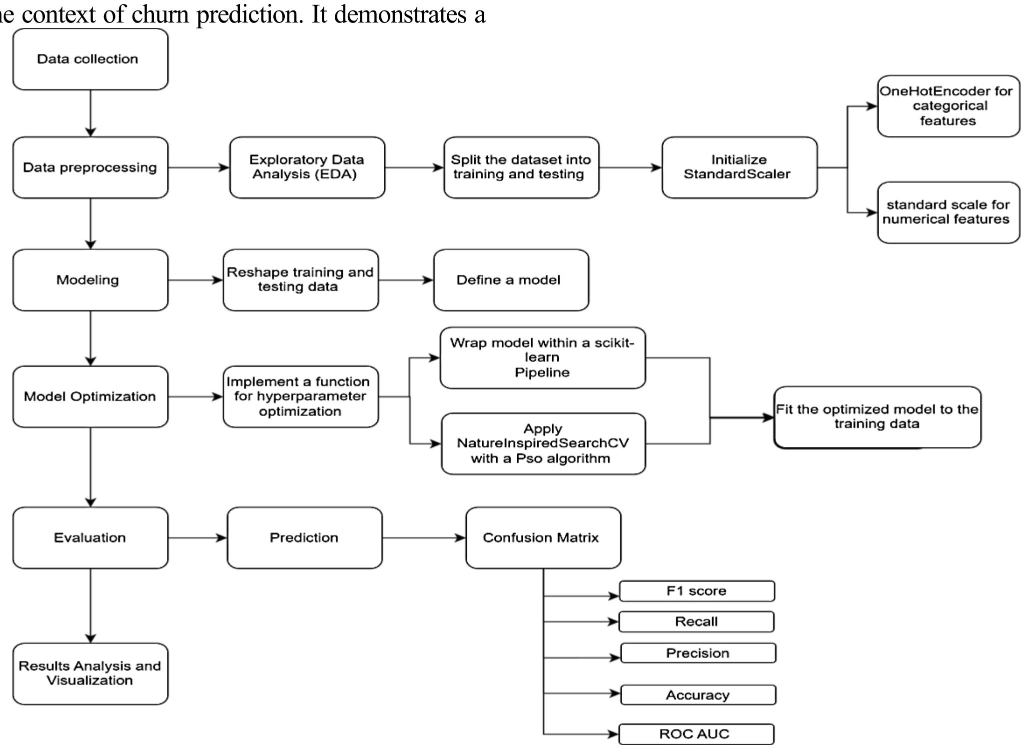

Fig. 1 Proposed system processes. Researcher's reference

The following section provides a concise pseudocode representation of the entire model development process

Pseudocode for Data Preparation and Model Development Process
A. Data Preparation and Model Development Process: Import necessary libraries for data handling (pandas, numpy), preprocessing (scikit-learn), and model building (keras, tensorflow). Load dataset from 'dataset.csv' into a DataFrame, ensuring integrity and accessibility. **B. Data Preprocessing:** Conduct Exploratory Data Analysis (EDA) to scrutinize dataset characteristics, missing values, outliers, and discern patterns. Split dataset into 'train_set' and 'test_set' for unbiased model evaluation. Initialize preprocessing utilities: a. 'StandardScaler' for normalization of numerical features. b. 'OneHotEncoder' for encoding categorical features. Categorize features: a. Categorical features for 'OneHotEncoder'. b. Numerical features for 'StandardScaler'. Apply 'ColumnTransformer': a. Fit on 'train_set' and transform both 'train_set' and 'test_set'. C. Model Preparation: Reshape 'train_set' and 'test_set' to conform with neural network input structure. Define neural network with CNN, GRU, and LSTM layers to capture data patterns. Wrap model in 'KerasClassifier' for compatibility with scikit-learn. **D. Model Optimization:** Implement PSO-based optimization function:

a. Embed model within a scikit-learn 'Pipeline'.
b. Apply 'NatureInspiredSearchCV' with PSO for hyperparameter tuning.
Train model on 'train_set', ensuring robustness and generalizability.
E. Model Evaluation:
Assess model with 'train_set' and 'test_set' using metrics: accuracy, precision, recall, F1, and ROC AUC.
Document optimal hyperparameters post-optimization.
F. Results Analysis and Visualization

4-1- Dataset

This study utilizes two diverse datasets supported by the ability to perform more extensive analysis on churn prediction in the telecom industry. The first one is Cell2Cell and is often used in CRM research as a model. Its dataset contained about 71,047 instances, with each one represented by 58 different attributes describing various aspects of user interaction, service consumption, and personal identification. The data was provided by the Teradata Center for Customer Relationship Management at Duke University. This allowed the research to reach a deeper understanding of user interactions and fields where retention strategies might be applicable, such as the high-competitive telecom sector. [22], [23].
The second utilized dataset is our modified version of a public IBM Telco Customer Churn dataset that we changed by adding more fields and by modifications to make it closer to real. This dataset covers a wide variety of fields regarding customer attributes for a telecommunication company and allows us to make a reasonable concern of a relationship between customer actions and churn. Our version of a public “JB Link Customer Churn Problem” use-case covers the story of a budding California-based telecom provider, present in more than 1000 cities in 1600 zip codes. Even though JB Link has shown fast growth with a vibrant sales team that signed up many customers, in the past quarter, only 43% of new customers were retained. [22], [23].
Collected data, which was a random sample of 7,043 customers would be an invaluable source of information for our data science team. Not only would it help to deconstruct the driving factors behind the high churn rate but also form the basis of the machine-learning model, which accurately predicts which customers are likely to churn. The latter would, in turn, provide the basis for an individualized retention strategy, which would greatly support the overarching task force of the JB Link to enhance customer retention [22], [23].
The analysis of the Cell2Cell data with the IBM Telco Customer Churn data would serve as both mutually confirming and opposing data. For instance, both data collections contain the data on the phone calls and other forms of communication but for different demographics and scales of operation. Furthermore, three sampling techniques would ensure an in-depth view of all data aspects. Overall, the research provides innovative approaches, which may assist telecommunication companies in understanding their customers better and subsequently reducing churn rates.

Table 2: Characteristics of Datasets

Characteristics	Cell2Cell	IBM Telco
Total of features	58	21
Total of customers	7,043	7043
Missing value	Yes	Yes
Churn	28.8%	25.5%
Not churn	71.2%	73.5%
Data distribution	Imbalanced	Imbalanced
Categorical features	23	17
Numerical features	35	4
Dependent feature	1	1
Independent features	57	20

4-2- Pre-processing

In the domain of customer churn prediction, data preprocessing is a significant step with the potential to dramatically impact the performance of predictive models. To this end, the model proposed for predicting customer churn places heavy emphasis on a careful data preprocessing phase with the goal of meticulously preparing the data to draw out maximum model performance. This preprocessing phase is designed with the peculiarities specific to telecom datasets in mind, and accounts for the treatment of missing values, the encoding of categorical variables, and normalizing features to a uniform scale.
The process starts with an Exploratory Data Analysis (EDA). We need to gain some insights about dataset’s characteristics, such as distributions, missing values, outliers, and detectable patterns. This step is critical for understanding the underlying structure of the data as well as to guide our initial preprocessing decisions. Then, we split the dataset into training and testing sets, in order to ensure an unbiased evaluation of the model performance. To manage the fact that our dataset is quite diverse, we initialize StandardScaler and OneHotEncoder. StandardScaler will be used in order to normalize numerical features aiming for a mean of zero and a variance of one, so that we can avoid inconsistencies from features that have different scales. We will simultaneously transform our categorical features into a suitable format for the model applying OneHotEncoder, which will also handle a strategic approach to dealing with unknown categories.

The importance of feature identification in this phase cannot be overstated since it is necessary to categorize features as numerical and categorical, based on their intrinsic nature. This categorization is key because different transformations need to be applied to different feature types. This is seamlessly managed by the ColumnTransformer utility, which applies OneHotEncoder to categorical features and StandardScaler to numerical ones. This utility is applied to the training data so that it learns the transformations that need to be applied, and they are then applied consistently to both the training and testing sets, ensuring that the data is consistent and the model is reliable. The preprocessing phase of the proposed model underlines the numerous meticulous efforts that are necessary before deep learning techniques can be used for churn prediction. By meticulously dealing with issues around data quality and ensuring that the dataset is prepared optimally for training the model, this phase sets the groundwork required to build a churn prediction model that is accurate and robust. This approach doesn't just substantially improve model performance, but can also offer valuable insights to the larger predictive analytics community around useful approaches to data preprocessing.

4-3- Conceptual Framework of the Proposed Model

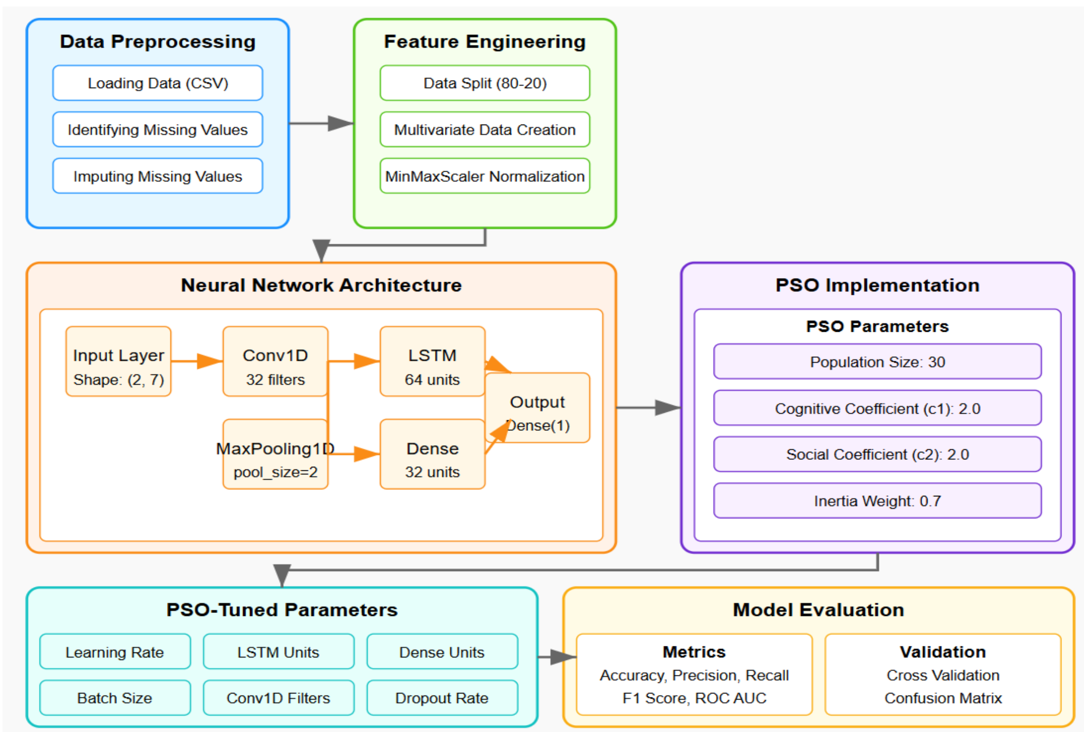

Fig. 2 Conceptual Model of Proposed Composite Deep Learning Approach Integrated with PSO

The proposed conceptual model shown in Figure ٢ highlights the broad workflow designed for the prophetic function, which reflects nervous network architecture design, PSO-powered hyperparameter optimization clearly reflects sequential processes from data shift and functional technique. This visualization provides a clear understanding of the internal function of the model, addresses the reviewers' suggestions properly for a detailed functioning explanation.

4-4- Model Preparation

4-4-1- Reshaping Data:

To process the data, the initial step is to reshape data. Both the training and testing datasets are reshaped according to the input requirements of the neural networks. The data are three-dimensional for CNNs and have the sequences for RNNs like GRU and LSTM. It is important to construct the data in such a way that the data supports extracting the spatial features and, at the same time, the data structure preserves the temporal sequence integrity. Consequently, the neural network learns both the immediate and contextual information that is available in the dataset. This step is important because the ability to learn from the immediate and contextual information that is available in the dataset is important for predicting the customer churn with high accuracy.

4-4-2- Architecture Selection Methodology

The selection of neural network components for our composite model follows a systematic approach based on the specific characteristics of customer churn prediction requirements and the nature of telecom datasets.

Convolutional Neural Networks (CNN) Selection: CNNs were integrated to capture spatial relationships and local feature patterns within customer interaction data. The hierarchical feature extraction capability of CNNs effectively identifies usage patterns such as call frequency clusters, data consumption trends, and service interaction sequences that traditional methods might overlook.

Selection of the Gated Recurrent Unit (GRU): The decision to use GRUs in preference to standard RNNs was taken because they are better at handling problems related to "vanishing gradient" – while still being much simpler computationally than LSTMs. With a gating mechanism that only lets some information through, it's easy for the model to pick out just what it needs from the mishmash of customer records and spit it back at everyone else in its own intelligible form. The idea that short-term behavioral patterns precede churn is something which detractors are simply not willing to swallow.

Long Short-Term Memory (LSTM) Selection: When GRUs fell short will be captured the long-term time a connection of many billing cycles or prolonged use periods in progress. The forget gate mechanism inside the dynamic recurrent network structure proves so useful for identifying the gradual behavioral changes that span months and are always critical indicators of impending churn.

Particle Swarm Optimization (PSO) Selection: PSO was chosen over other evolutionary algorithms such as Genetic Algorithms or Simulated Annealing, mainly because in these higher-dimensional hyperparameter spaces it has been shown to be most effective, and has certain characteristics which make it converge faster. Unlike grid search or random search methods, PSO provides intelligent exploration of the hyperparameter landscape while maintaining computational feasibility.

4-4-3- Defining the Model

The core of the proposed solution is to adopt a hybrid neural network that combines the strengths of GRU, CNN, and LSTM layers. CNN layers are good at learning the hierarchical spatial features from customer usage patterns like the frequency of calls, data usage, and interaction with the services. After the CNN layers, the LSTM and GRU layers are used to learn the long-term and short-term temporal dependencies, respectively. The combination allows the neural network to learn customer's behavior over time, the evolution of the usage patterns, and the impact of the specific events/interactions. The architecture of the model is carefully designed to balance the learning capacity and computational efficiency in order to be powerful and at the same time practical to be used in the real-world applications.

4-4-4- Integration with KerasClassifier:

The KerasClassifier wraps the model so that it can be used with scikit-learn's (very useful!) extensive suite of utilities for model evaluation, hyperparameter tuning, cross-validation, etc. When using any in-house neural network model with scikit-learn, the model must be wrapped before it can be used. There is a lot of interest in using machine learning models, especially deep learning models, for predictive modeling in a business environment. One can leverage their data science skills in Python to the fullest extent by integrating a keras model with the broader Python machine learning ecosystem, especially scikit-learn. This will not only ease the model evaluation process as scikit-learn has robust methodologies for model evaluation, but will also realize the full potential of a neural network model.

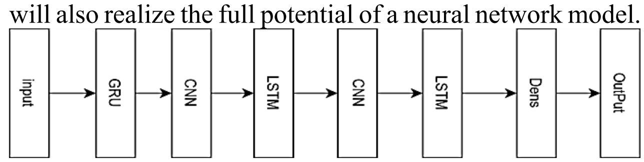

Fig. 3 Layers of the proposed model. Researcher's reference

4-4-5- Composite Neural Network Architecture

The proposed general deep learning architecture consists of several sequential teams, which are clearly designed to use both temporary and spatial functions from customer interaction data. The architecture begins with a GRA layer with Gay -Recorded Unit to capture short -term sequential addiction. Then a fixed nerve network (CNN) layers are used to remove spatial functions from data. Then identifies a long -lasting short -term memory (LSTM) layer long -term sequential patterns. Another CNN team follows to catch more complex patterns. Finally, a second LSTM layer with return_chats = = error is used to consolidate the information learned to a comprehensive functional vector. A close layer of a sigmoid activation function acts as the final output team for binary classification of customer whores.

4-4-6- Model Integration and Computational Complexity

The composite deep learning model is constructed with various layered neural network components in an order that can be used to capture the spatial and temporal structure. The following is the workflow of how the integration is implemented:

Sequential Integration Process: The proposed model consists of five consecutive processing stages including. First, a GRU layer with 75-80 neurons (dataset optimization dependent) models short-term sequential relationships from the preprocessed customer interaction data. Afterward, the GRU output tensor serves as input for a CNN layer with 32 filters and a 3-size kernel, which captures spatial information and local contexts of the sentence representations. Then, there is an LSTM layer with the same number of neurons in the GRU layer which takes the CNN output to capture the long-term temporal dependencies. Another CNN layer with 16 filtering is performed to refine the feature extraction. Ultimately a second LSTM layer, this time return_sequences=False then pools all the representations into a final feature vector for the sigmoid classification layer.

Computational Complexity Analysis:

Time Complexity: Its time complexity is in O(n×m×k), with n being the number of training samples, m the sequence length (number of features) and k the total number of neurons from all layers. Both the GRU and LSTM layers have a complexity of O(n×m×h), where h is the number of hidden units, and CNN layers an O(n×m×f×s) complexity, where f is the number of filters and s is the kernel size.

Space Complexity:

Our model which is of space complexity O(hxl), in which h is the max number of hidden units per layer, and l is the count of total number of layers. The composite architecture requires approximately 2.3 million parameters for the Cell2Cell dataset configuration, and 2.1m parameters for the IBM Telco setup, while the composite model is stored to memory as 9.2MB and 8.4MB respectively.

4-5- Model Optimization

In the context of customer churn prediction, model optimization, which may be defined as the process of refining a model using historical data, hoping that the model will then perform better on new data, marks an important stage of the pursuit of predictive excellence. This section describes the methodological framework used to improve the predictive accuracy of the composite neural network model by leveraging the power of evolutionary computation to fine-tune its hyperparameters.

Integration of PSO into the Composite Deep Learning Model

In the proposed method, the Particle Swarm Optimization (PSO) was fully integrated into the general training process for deep learning. Each particle in the PSO algorithm represents a unique combination of hyper lovers, including activation functions (ReLU or SELU), methods of regularization (L1, L2, Elastic Net), learning speed, per layer per layer number and optimize (Adams, RMSProp or AdaGrad). During each repetition, the nerve network is trained using these hyperparameters, and performance is evaluated based on matrix-like accuracy, precision, recalling, F1 scores and ROC-AUC. Based on this evaluation, PSO constantly updates the individual best (Pbest) and Gbest hyperparameter sets. This repetition optimizes continues to convergence and ensures the discovery of the optimal hyperparameter configuration. The final nerve network is then trained with this optimal set of hyperparameter.

Evolutionary Algorithm- Driven Hyperparameter Optimization:

At the core of this optimization phase is the implementation of a function that builds on the capabilities of evolutionary algorithms, a class of optimization techniques, which are inspired by the evolutionary processes that occur in natural ecosystems. These algorithms manipulate a population of candidate solutions to a given computational problem, using the principles of selection, crossover and mutation, emulating the survival-of-the-fittest drive that is inherent in biological evolution, to produce successive generations of the population with an increasingly improved ability to solve the problem at hand. Applying the function to the neural network model yielded an optimized version of the model.

Integration into a Computational Pipeline:

To allow for a seamless and efficient optimization process, the composite neural network model is encapsulated within a scikit-learn Pipeline. This encapsulation allows for preprocessing and modeling steps to be properly applied while guaranteeing that the model's structure and parameters are consistently maintained during the optimization process. The pipeline framework provides a structured environment where the model can be freely adjusted and evaluated, in this way maintaining the integrity of the optimization workflow.

At the core of the optimization function, NatureInspiredSearchCV is a dedicated component for performing hyperparameter tuning based on nature-inspired algorithms. For the purposes of this story, Particle Swarm Optimization (PSO) has been chosen as the evolutionary mechanism of choice, which has demonstrated effectiveness in navigating complex, high-dimensional search spaces through a combination of exploration and exploitation.

One key thing to note is that the application of PSO within this context must be carefully configured. The population size and generation count are critical parameters that will guide the evolutionary process. Additionally, the early stopping criteria must be configured in order to ensure that the PSO algorithm efficiently converges to the optimal set of hyperparameters without running over the computational redundancy or overfitting.

This section outlines a substantial academic quest intending to further the horizons of forecasting accuracy. The involvement of evolutionary algorithms in fine-tuning neural network models for churn prediction endeavors to contribute to this effort. This goes far beyond the simple enhancement of a model's performance through meticulous adjustment of its hyperparameters. It is also a substantial contribution to the ongoing debate about the appropriate place of bio-inspired computational methodologies in the realm of deep learning and customer attrition prediction. This optimization phase is where the principles of computational intelligence very directly intersect those of machine learning, signaling a new age in predictive analytics and particularly in the rapidly-evolving domain of the telecommunications industry. In short, this section describes the painstaking precision and academic rigor applied to the enhancement of the composite neural network model for churn prediction. The objective here is to improve the model's predictive accuracy with a view to providing critical insights for telecommunication entities, to diminish the scale of customer churn, and enhance customer loyalty. By deploying evolutionary algorithms, and particularly Particle Swarm Optimization (PSO), within a clearly delineated computational framework, contributions are made to this end.

4-5-1- PSO Selection Rationale

The PSO was chosen as the hyperparameters optimization algorithm according to several key elements associated with deep learning optimization problems. Grid search and random search, which are traditional optimization search methods, have exponential time complexity in high-dimensional hyperparameter spaces. Grid search is computationally infeasible with our five-dimensional hyperparameter space (activation functions, regularization methods, layers shapes, learning rates, and optimizers) and random search is not intelligent in terms of exploration.
PSO has several advantages over other evolutionary algorithms. When contrasted with Genetic Algorithm PSO exhibits a more rapid convergence and less function evaluations because of its velocity-controlled element motion. PSO keeps the diversity of the search population and avoids falling into local optimal solutions more than the Simulated Annealing. Bayesian Optimization works well for continuous parameters, but it fails on mixed discrete-continuous spaces as of our hyperparameter landscape.

4-5-2- PSO-Optimized Parameters Specification

The PSO method optimizes five important hyperparameter groups that have a direct impact on the performance of the model and learning curves. The choice of the activation function ReLU and SELU regulates the non-linear transformation capacity for each layer, while ReLU is computational efficient, SELU has a self-normalizing property. Optimizing the regularization technique among L1, L2, and Elastic Net helps prevent overfitting, as L1 enables sparsity features, L2 favors smaller weights, and Elastic Net mixes both mechanisms.
Optimal number of neurons in ranges of 25, 50, 75, and 100 per layer, is chosen in order to balance model capacity and extreme computational requirements. Optimizing learning rate between 0.01, 0.001 and 0.005 affects convergence time and stability. Optimization is achieved using Adam, RMSProp, and AdaGrad and the choice of optimizer defines the gradient descent strategy for which we have used different adaptive learning rate mechanisms that are appropriate for different data.

4-6- Model Evaluation

Key to the successful completion of the model optimization phase is embarking on the crucial journey that is the evaluation of the performance of our neural network model. For, it is at this juncture where we delve into the ultimate test, that being an exhaustive interrogation of our model's ability to generalize and correctly predict customer churn across a wide variety of datasets. We draw from a suite of performance metrics that we use as proxies to gauge the model's effectiveness, assessing it on both the training and testing datasets.

Delineating Performance Through Metrics:

- Accuracy Score: Accuracy is at the nucleus of the evaluation metrics. It looks at the model's ability to correctly make a prediction. More specifically, accuracy: the number of correct predictions made as a proportion of all predictions. Accuracy provides a high-level view of the model's predictive capacity. It represents (roughly) the percentage of true positives and true negatives the model was able to generate among all predictions. It is very useful when we are trying to measure the performance of a model that has not an inherent imbalance between the classes. Especially, when a business is trying to analyze its customer spectrum to determine retention and churn[5].

$$\text{Accuracy}= \frac{\text{True Positive} + \text{True Negative}}{\text{True Positive} + \text{True Negative} + \text{False Positive} + \text{False Negative}} \tag{3}$$

- Precision Score: Precision gets deeper into the model’s exactitude and centers in on its ability to identify churn correctly when it predicts churn. This is particularly useful in situations where there is a high cost associated with false positives, such as identifying churn when it does not exist, as the model’s precision will reflect how well it is genuinely able to discriminate among the cases where churn is true[24].

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} \tag{4}$$

- Recall Score: Complementing precision, recall measures the model's sensitivity—the proportion of actual churn cases it successfully detects. In the churn prediction domain, a high recall indicates the model's adeptness in capturing the majority of churn instances, ensuring minimal missed opportunities for intervention[24].

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \quad (5)$$

- F1 Score: The harmonization of precision and recall is embodied in the F1 score, a balanced measure that encapsulates the trade-off between the two. It serves as a single metric that condenses the essence of both precision and recall, offering a holistic view of the model's performance in scenarios where both false positives and false negatives carry significant implications[5].

$$\text{F1 Score} = \frac{2\times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (6)$$

- ROC-AUC Score[5]: The Area Under the Receiver Operating Characteristic Curve (ROC-AUC) transcends mere accuracy, providing a nuanced evaluation of the model's discriminative ability across various threshold settings. As customer behavior professionals, we understand that – depending on the specifics of any given customer retention or churn management campaign – we may be permitted some error as we distinguish between likely and less-likely churners, but that we must work diligently to flag as many instances of churn as possible. The ROC-AUC is invaluable because it shows us the model's performance in discriminating between churn and non-churn instances as we dial our certainty up or down inclining towards cautious accuracy or the broad-catching, false-alarm-prone net we might set if our only concern were to ensure we tagged every last instance of churn!

$$\text{ROC-AUC} = \frac{1}{2} \times (\text{ Sensitivity} + \text{Specificity }) \quad (7)$$

5- Results Analysis

Our aim was to better the prediction of customer churn in the telecommunications sector by combining Particle Swarm Optimization with cutting-edge composite deep learning models. The crux of our study focused on improving the hyperparameters of these models, which is a fundamentally crucial factor in determining their optimal performance and accuracy. This section, therefore, provides an in-depth examination of the PSO algorithm and the strategic tuning of parameters and optimization strategies that were vital in enhancing our model's prediction. From here, we will examine the specific target hyperparameters optimized using PSO, and which of these hyperparameters significantly contributed to a refined prediction of churn. For simulations designed to fine-tune the deep learning model, we relied on Python as a programming language due to its easy syntax, and TensorFlow and Keras were critical for developing and training the model. Overall, these frameworks are until to building in the deep neural network's environment, practitioner and satisfied complementing them to Scikit-learn for pre-processing and evaluation of the tools. We also used the Python programming process but others powerful packages such as NiaPy and sklearn_nature_inspired_algorithms to optimize PSO algorithms for practical implementation of hyperparameters. This approach fuses the best of machine learning with nature-inspired computing expertise, resulting in a comprehensive solution for solving customer churn. These have never been made before as this refined approach achieved detailed analysis and high forecast accuracy. Subsequent sections will further explore the results of our studies scrutinizing various empirical simulation results that underscore the most extensive model performance and the impact of the computational approach described above.

Explanation of PSO Algorithm Parameters:

Table 3: Particle Swarm Optimization (PSO) Algorithm Parameters

Parameter	Description	Value
Np	Population Size	50
***C*۱**	Cognitive Coefficient	2.0
***C*۲**	Social Coefficient	2.0
w	Inertia Weight	0.9 to 0.4 (decreasing)
Max_{iter}	Maximum Number of Iterations	100

In summary, the essence of our hyperparameter tuning approach with the Particle Swarm Optimization algorithm that strikes a perfect balance between simplicity and depth can be distilled into the following salient characteristics:

- **Population Size**: We selected a swarm of 50 particles, each representing a comprehensive hyperparameter solution. This number is deemed suitable for comprehensive exploration and discovery while ensuring that computational resources are not overburdened, providing an efficient search of the hyperparameter space.
- **Cognitive Coefficient 1 and Social Coefficient**: 2.0 was selected for both coefficients as they reflect the dual determinants to guide the action of a single particle. This ratio ensures one-part concentrates on personal executory experience, while another maintains a view on collective experience in a balanced execution manner.
- **Inertia Weight**: The inertia weight was gradually reduced from 0.9 to 0.4 to decide the velocity with which each particle could transition to new solutions. Thus, the particle was allowed to have a broad initial approach and progressively removed from a position to ensure they selected the most promising part of the solution.
- **Maximum Number of Iterations**: 100 iterations were considered appropriate for the selection process down to manageable limits.

Hyperparameter Selection for PSO-Driven Optimization

In our ongoing quest to elevate the predictive accuracy of our composite deep learning model for customer churn prediction, we judiciously handpick a suite of hyperparameters as candidates for optimization through the Particle Swarm Optimization (PSO) algorithm. The chosen hyperparameters are critical as they govern the learning dynamics of the model and its ability to capture the intricate patterns of customer behavior. Here are the hyperparameters currently under consideration:

- **Activation Functions**: The activation function is used to introduce non-linearity to the neural network, allowing it to learn complex relational patterns. The ReLU (Rectified Linear Unit) and SELU (Scaled Exponential Linear Unit) activation functions are considered for our model due to their ability to mitigate the vanishing gradient problems and facilitate faster convergence.
- **Regularization Techniques**: To combat overfitting and ensure the generalizability of the model, L1 (Lasso), L2 (Ridge), and Elastic Net regularization techniques are being investigated. Regularization is a method used to introduce additional penalties on the magnitude of the coefficients, forcing the learning algorithm to shrink them toward zero. L1 regularization promotes sparsity and can be used for feature selection tasks. L2 regularization is similar to the L1, but it encourages smaller coefficients and is used to penalize larger coefficients more heavily. The Elastic Net is a hybrid that blends both L1 and L2 regularization attributes.
- **Neurons per Layer**: The number of neurons in a layer is crucial for the model's capacity to learn; too few can cause underfitting, and too many can lead to overfitting. We choose to evaluate configurations with 25, 50, 75, and 100 neurons per layer to strike a balance between model complexity and computational efficiency.
- **Learning Rate**: This hyperparameter determines the step size at each iteration while moving toward a minimum of a loss function. We try values of 0.01, 0.001, and 0.005 to ensure that we perform a nuanced exploration of the learning rate space in an effort to find a sweet spot, optimizing for learning speed and stability.
- Optimizers play a critical role in minimizing the loss function and thereby, directly impacting the performance of the model. In our case, we have included Adam, RMSProp, and AdaGrad in our optimization process, with each having its own unique approach for adjusting the learning rate during training catering to different aspects of convergence and computational efficiency.

The Particle Swarm Optimization (PSO) algorithm is capable of traversing the multidimensional hyperparameter space defined by these candidates in search of that configuration that yields the best possible performance in terms of its predictive accuracy, precision, recall, F1 score, and ROC AUC score. The ultimate goal is to discover an optimal set of hyperparameters that allows us to balance our model's complexity against its capability to generalize well to new data, resulting in churn predictions that are even more accurate and actionable.

Table 4: Hyperparameters used in the model

Hyperparameter	Options
Activation Function	ReLU, SELU
Regularization Method	L1(Lasso), L2 (Ridge), Elastic Net
Neurons per Layer	25, 50, 75, 100
Learning Rate	0.01, 0.001, 0.005
Optimizers	Adam, RMSProp, AdaGrad

In the first phase of our experimentation, we focused on leveraging the PSO algorithm to meticulously select optimal hyperparameters. The aim was to determine a configuration capable of maximizing the predictive accuracy of our model, while guaranteeing generalizability. The results of our optimization process are outlined below: Our in-depth analysis utilizing the Particle Swarm Optimization (PSO) algorithm has led to the identification of an optimal hyperparameter configuration that markedly improves the churn prediction capabilities of our deep learning models. The configurations detailed below have been tailored specifically for the Cell2Cell and IBM Telco datasets, showcasing the algorithm's robustness and adaptability.

Optimal Hyperparameter Configuration for Cell2Cell Dataset

The PSO algorithm found the following hyperparameter settings to produce the optimum model for the Cell2Cell dataset. The application of the ReLU function enabled our model to effectively capture the nonlinearity of the given data while avoiding the vanishing gradient problem. Regularization in this case, L2 regularization removed the overfitting in the data to improve the model's generalization through penalties to the coefficient sizes. We deduced that there should be 75 neurons within each layer to provide the right balance of model capacity to identify patterns in inputs without demanding extensive computation. We selected a learning rate of 0.005 as it was the best trade-off, sufficiently fast to allow for reasonable convergence times and slow enough for a robust generalization. We picked the Adam optimizer due to its adaptive nature of finding the global minimum of the loss function, allowing for relatively fewer iterations to converge than SGD.

Optimal Hyperparameter Configuration for IBM Telco Dataset

The PSO algorithm when applied to the IBM Telco dataset revealed a more refined change in hyperparameter settings that would fit the dataset's specific characteristics. The following are the changes that were affected on the Cell2Cell without impacting the output structure: The ReLU function has enabled efficient processing of non-linear relationships; hence, it remained the activation function of choice. The regularization method was thus L2 as per the Cell2Cell findings since they facilitate the model's generalizability; The neurons per layer were optimized at 80 since it had the most intricate patterns between the other two datasets. The learning rate was optimized with the applied PSO algorithm to a 0.0045 which helped in achieving an accurate rate of convergence in running time also avoiding overfitting. The optimizer remained Adam from the information given to affect a quick mode of layers' convergence on the nodes.

Comparative Tables for Hyperparameter Settings

For the sake of clarity and comparability, we have compiled the optimal hyperparameters for both datasets in Table 5 and Table 6.

Table 5: Optimal Hyperparameters for the Cell2Cell Dataset Using the PSO Algorithm

Hyperparameter	Optimal Value (Cell2Cell)
Activation Function	ReLU
Regularization Method	L2 (Ridge)
Neurons per Layer	75
Learning Rate	0.005
Optimizer	Adam

Table 6: Optimal Hyperparameters for the IBM Telco Dataset Using the PSO Algorithm

Hyperparameter	Optimal Value (IBM Telco)
Activation Function	ReLU
Regularization Method	L2 (Ridge)
Neurons per Layer	80
Learning Rate	0.0045
Optimizer	Adam

These optimized configurations epitomize the PSO approach's efficacy in traversing the complex hyperparameter clustering space and the blending of artificial intelligence and deep learning paradigms. It is our endeavor to acclimate the model and prediction parameters to churn either computationally or operationally, with remarkable advances in precision and implementation. The model configuration with PSO, as shown in Table 6 and Table 7, had an incredible design outcome for optimal Cell2Cell and IBM Telco. This result is revealed in the training and testing phases, as demonstrated in performance statistics, resulting aspiration and baseline configurations from the model.

Table 7: Performance Metrics for the Cell2Cell Dataset

Metric	Training Data	Testing Data
Accuracy	93.8%	93.24%
Precision	90.3%	89.00%
Recall	92.2%	91.00%
F1 Score	91.5%	90.00%
ROC AUC	94.15%	93.24%

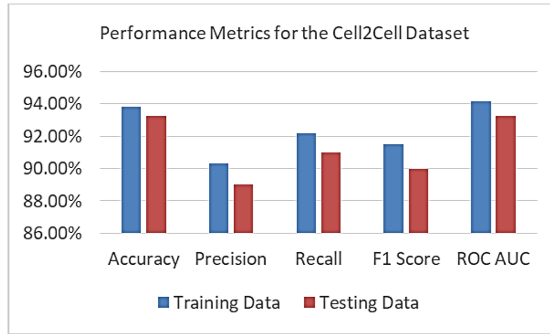

Fig. 4 Performance Metrics for the Cell2Cell Dataset

Table 8: Performance Metrics for the IBM Telco Dataset

Metric	Training Data	Testing Data
Accuracy	93.3%	93.24%
Precision	89.8%	89.00%
Recall	91.7%	90.50%
F1 Score	90.5%	89.75%
ROC AUC	93.7%	93.10%

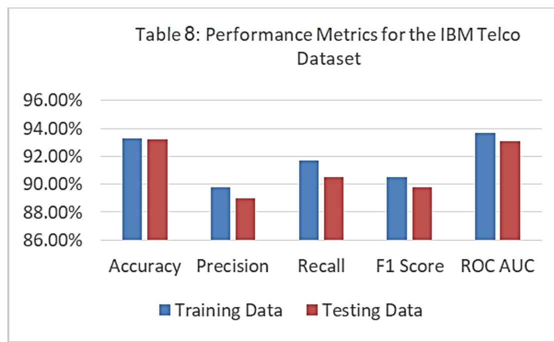

Fig. 5 Performance Metrics for the IBM Telco Dataset

The optimized models demonstrate significant ability to separate churn from retention cases; the performance metrics indicate the model's strong balance between overfitting and underfitting. This is crucial for dealing with the variance that real-world data possesses and suggests the PSO algorithm's benefits in model tuning.

6- Discussion and Interpretation

In a rigorous comparative analysis, our proposed version changed into evaluated towards traditional deep getting to know architectures—along with CNN_LSTM, LSTM, GRU, and LSRM_GRU—in addition to different techniques which includes KNN, XG_BOOST, DEEP BP-ANN, BiLSTM-CNN, and Decision Tree. The results summarized in Table 9 (Cell2Cell dataset) and Table 10 (IBM Telco dataset) Truely show the strengths and weaknesses of each approach.

For the Cell2Cell dataset, the proposed version executed an ROC-AUC of 0.932, an F1 Score of 0.9, and a Recall of 0.91. These metrics significantly exceed those of the conventional techniques. For example, while LSTM and GRU seize sequential styles nicely, they're less effective in concurrently extracting spatial capabilities compared to our composite structure. Moreover, strategies like DEEP BP-ANN and LSRM_GRU, despite the fact that aggressive in some metrics, do now not combine hyperparameter optimization as efficiently as our method. The inferior overall performance of models including KNN, XG_BOOST, BiLSTM-CNN, and Decision Tree similarly underlines the benefit of our version's comprehensive design in coping with the complicated styles in patron churn statistics.

Similarly, on the IBM Telco dataset, the proposed model performs better in comparative methods, ROC-AUC of 0.93, F1 points of 0.895 and a recall of 0.905. Better performance can be attributed to effective integration of Particle Swarm Optimization (PSO) mainly for hyperparameter attitude, which means that our general deep learning architecture can better adapt for data. This integration increases both spatial traction (through CNN layers) and temporary addiction learning (through horror and LSTM layers).

Overall, these conclusions emphasize that the proposed model not only gets high accuracy and balanced performance matrix, but also provides strong adaptability for complex data sets, which emphasizes the relevance of current research trends.

Table 9: Cell2Cell Dataset Performance

Algorithm	ROC-AUC	F1 Score	Recall	Precision	Accuracy
CNN_LSTM	0.77	0.74	0.81	0.80	0.81
LSTM	0.79	0.78	0.85	0.84	0.83
GRU	0.79	0.75	0.84	0.83	0.82
LSRM_GRU	0.81	0.79	0.86	0.86	0.82
KNN[3], [25]	0.63	0.66	0.72	0.61	0.63
XG_BOOST[3]	0.72	072	0.75	0.7	0.72
DEEP BP-ANN[3]	0.79	0.81	0.89	0.72	0.79
BiLSTM-CNN[4]	0.66	0.62	0.61	0.62	0.78
Decision Tree[4]	0.58	0.57	0.59	0.56	0.76
Proposed Model	0.932	0.90	0.91	0.89	0.832

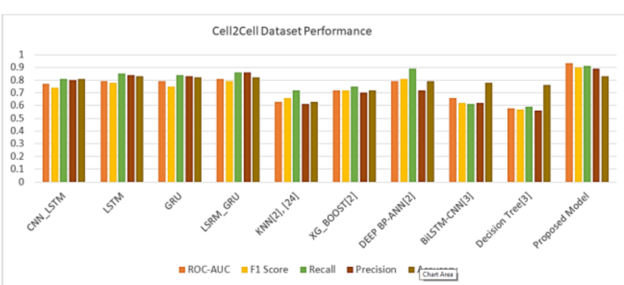

Fig. 6 Cell2Cell Dataset Performance

For the IBM Telco dataset, the proposed model again outperforms the baseline architectures, as seen in the following table:

Table 10: IBM Telco Dataset Performance

Algorithm	ROC-AUC	F1 Score	Recall	Precision	Accuracy
CNN_LSTM	0.77	0.74	0.81	0.80	0.81
LSTM	0.79	0.78	0.85	0.84	0.83
GRU	0.79	0.75	0.84	0.83	0.82
LSRM_GRU	0.81	0.79	0.86	0.86	0.82
KNN[3], [25]	0.76	0.78	0.84	0.73	0.76
XG_BOOST[3]	0.85	0.86	0.9	0.81	.085
DEEP BP-ANN[3]	0.88	0.88	0.91	0.84	0.88
BiLSTM-CNN[4]	0.70	0.65	0.64	0.66	0.81
Decision Tree[4]	0.6	0.59	0.62	0.57	0.78
Proposed Model	0.93	0.895	0.905	0.89	0.93

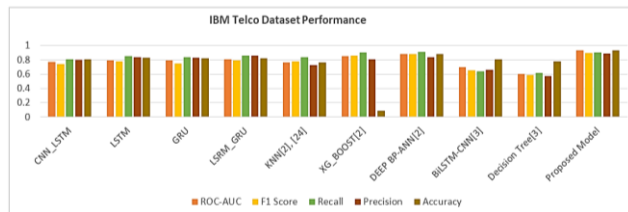

Fig. 7 IBM Telco Dataset Performance

The model's predictive prowess is confirmed by the ROC-AUC score of 0.93 and the accuracy of 0.93 on the IBM Telco dataset, demonstrating remarkable consistency and the model's robust generalization across distinct datasets. When juxtaposing the model's performance across both datasets, the following trends and consistencies are observed:

Table 11: Comparative Analysis

Dataset	ROC-AUC	F1 Score	Recall	Precision	Accuracy
Cell2Cell	0.932	0.90	0.91	0.89	0.832
IBM Telco	0.93	0.895	0.905	0.89	0.93

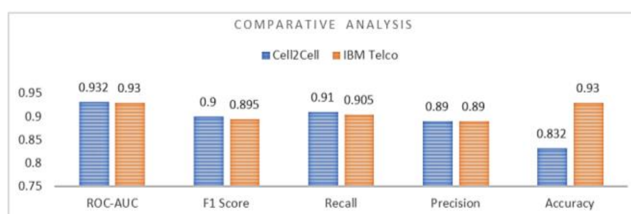

Fig. 8 Comparative Analysis

The proposed model exhibits slightly better precision and F1 score on the Cell2Cell dataset but shows a notably higher accuracy on the IBM Telco dataset. This demonstrates the model's adaptability and its capacity to maintain high levels of prediction quality, regardless of the dataset nuances. The results highlight the proposed model's capacity for discerning true positives, as evidenced by high recall values. Coupled with robust precision, it demonstrates the model's aptitude in accurately classifying customers who are most likely to churn, which is crucial for effective customer retention strategies.

Overall, the proposed model's superior performance metrics underline its efficacy in the customer churn prediction task, outpacing conventional deep learning models. It presents a significant leap forward in predictive accuracy and reliability, offering telecom operators a powerful tool to combat customer attrition. The balanced precision-recall and high accuracy confirm the model's applicability in real-world scenarios, promising a potential shift in how customer retention strategies are crafted and implemented.

7- Conclusion

Finally, this study addresses the constant challenge of grinding the customer sector by launching a new complex deep learning framework adapted through the Particle Swarm Optimization (PSO). By integrating a variety of nerve network architecture, our approach captures both spatial and cosmic functions found in customer data. Inclusion of the hyperparameter setting PSO allows the model dynamically to adapt to complex data patterns, increasing its future strength and generality.

Our findings display that the proposed technique considerably advances the ultra-modern in churn prediction compared to standard deep getting to know techniques. This innovative integration now not best streamlines the hyperparameter optimization system however also enables a balanced performance across more than one evaluation metrics. Moreover, the methodological contributions of this take a look at lay a stable foundation for similarly studies in adaptive and hybrid predictive fashions. Ultimately, this work offers valuable insights into the application of evolutionary algorithms within deep learning frameworks, underscoring their potential to transform client dating control practices and stimulate future improvements in predictive analytics.

To further advance churn prediction research and develop the proposed algorithm, there are a number of interesting paths for future exploration, including the following:

- Feature Set Expansion: Enrich the feature set to integrate additional customer data points, such as social media activity or call center interactions, which may unlock deeper behavioral insights affecting churn.
- Cross-Industry Validation: Test the developed model on separate telecom datasets, or alternatively on another industry facing high rates of customer churn, to determine the algorithm's robustness and generalization capabilities.
- Algorithmic Refinement: Experiment with more sophisticated variants of Particle Swarm Optimization, such as Quantum-behaved PSO or Hybrid PSO, both of which may offer improved global optimization and faster convergence.
- Hyperparameter Exploration: Further extend the hyperparameter tuning process for the ANN model across a broader range, as well as considering alternative nature-inspired optimization methodologies to discover the most efficient model configurations.

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Journal of Information Systems and Telecommunication
Vol.13, No.2, April-June 2025, 111-121
http://jist.acecr.org
ISSN 2322-1437 / EISSN:2345-2773

A Holistic Approach to Stress Identification: Integrating Questionnaires and Physiological Signals through Machine Learning

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Received: 14 Oct 2024/ Revised: 04 May 2025/ Accepted: 07 Jun 2025

Abstract

This research project presents a comprehensive methodology for stress identification by combining subjective self-report data and objective physiological signals. The proposed system employs a carefully designed questionnaire, tailored to different age groups, to enhance accuracy in stress assessment. Subjects respond to the questionnaire, providing valuable insights into their emotional well-being. Subsequently, physiological data is collected using an infrared (IR) sensor positioned beneath the wrist, close to the artery. The pulse data obtained is meticulously converted into a CSV file, allowing for efficient preprocessing. The preprocessing phase ensures the integrity of the data, preparing it for machine learning (ML) analysis. The study harnesses ML techniques, specifically SVM (Support Vector Machines) & KNN (K-Nearest Neighbors), to classify stress levels based on the pre-processed data. Through feature extraction, relevant patterns are identified, contributing to the accurate characterization of stress states. This integrative approach offers a robust framework for stress assessment, taking into account both subjective and physiological dimensions.
Results demonstrate promising accuracy levels: Support Vector Machine (SVM) Reached a level of precision of 0.98 (+/- 0.20), Decision Tree showed 0.93 (+/- 0.30), and K-Nearest Neighbors (KNN) reached 0.88 (+/- 0.44). It also implements the voting classifier for improved performance of 98.6% of accuracy. These findings underscore the effectiveness of the proposed methodology in accurately identifying stress levels. Integrating subjective insights with objective physiological data not only enhances stress identification but also offers a comprehension of the intricate correlation between mental states and physiological reactions. This comprehensive strategy holds substantial implications across diverse domains such as healthcare, psychology, and human-computer interaction.

Keywords: Stress Identification; PPG, Age-Specific Assessment; Data Preprocessing; SVM; Feature Extraction; Classification Techniques; KNN; Stress Assessment; Well-being.

1- Introduction

In today's fast-paced society, stress has become an unavoidable aspect of daily existence, impacting individuals of all age ranges. Acknowledging the crucial influence of stress on mental health and overall welfare, there is an increasing need for effective stress detection systems [1]. This research endeavors to present an innovative and integrative approach to stress assessment by combining self-reported data through a comprehensive questionnaire and physiological measurements using pulse data collected via an infrared (IR) sensor [2].

Stress, a complex physiological and psychological phenomenon, is often characterized by feelings of fear, anxiety, and helplessness [3]. Stressor is an event or situation due to which stress is generated. Stress may lead to damage of usual physical functions and as well as developing few pathological conditions [3].

The causes of stress are shown in figure 1. The stress is also of three different types, good stress, bad stress and neutral stress. Good stress, also called eustress, has a positive impact on your physiological conditions. It may improve your performance. One may get motivated in a few

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situations maybe like getting married or awarded. Bad stress, also called distress, may degrade one's performance. It has a bad impact on the physiological conditions. Examples are getting diagnosed with some disease, losing job, falling under some calamity. The neutral stress is also called neustress. It is associated with events which are not good, not bad for someone. Examples are storms in other countries, sudden increase in birthrate of your country.

If you know the stress symptoms, then treating stress becomes easy. Those can broadly be classified as cognitive, emotional, physical, and behavioral symptoms. The treatment of the stress can start only after stress detection. These symptoms are very important in the case of detection. These symptoms do change the physiological parameters of the individual.

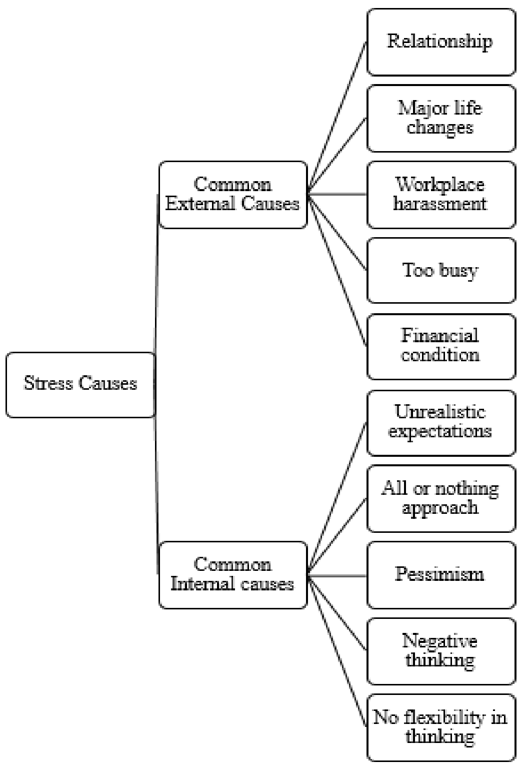

Figure 1. Causes of stress [3], [4]

It is well known fact that stress is a "flight – or – fight" kind of response. It changes the physical and physiological parameters in the human body and that's why stress stands out to be a very important thing to be cured. Figure 2 shows various symptoms related to stress. One needs to understand that one present situation may be very stressful for one individual and the same situation may be very challenging and motivating for another individual. And so, the response to the same situation is different from different individuals.

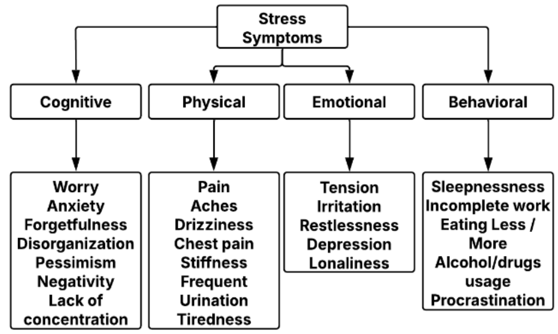

Figure 2. Stress Symptoms [3], [4]

In recent years, statistical data has highlighted the widespread prevalence of stress and its impact on individuals' well-being. This study aims to detect stress of an individual. As several individuals are suffering from stress, if it is detected well in advance and treated, then the impact of stress can be reduced. To ensure the accuracy and reliability of stress detection, our study employs a questionnaire tailored with the help of psychologists. The questionnaire delves into behavioral, emotional, and cognitive aspects related to test anxiety, procrastination, physical symptoms, and the overall impact of stress on academic and career pursuits. Respondents rate their experiences on a scale, providing a quantitative foundation for subsequent analysis. The physiological data collection involves the use of an IR sensor placed below the wrist, capturing pulse data through the underlying artery. Utilizing computational techniques such as SVM (Support Vector Machines) & KNN (K-Nearest Neighbors) in the realm of machine learning constitutes a fundamental aspect of our approach. These algorithms play a pivotal role in our classification tasks, assisting in identifying patterns and relationships within the pre-processed data. This facilitates the extraction of significant features that serve as indicators of stress, ultimately contributing to the development of a robust stress detection system. Our study innovates a different methodology to combine the psychological (through questionnaire response) and physiological (through the sensor placed on wrist pulse) parameters on one subject to detect the stress accurately for the treatment. The remaining article is arranged as, section II discourses the literature in the same area, section III presents the proposed work and its methodology, section IV deals with the results and its discussion, whereas section V concludes this article.

2- Literature Survey

Our review of the literature is organized into distinct sections, each focusing on critical aspects of our study. These categories include subjective evaluation for stress identification, physiological indicators for stress detection, machine learning methodologies for stress classification, feature extraction and selection techniques in stress analysis, and age-specific approaches to stress assessment. Each division offers valuable insights into comprehending and managing stress from various angles, spanning subjective perceptions to objective physiological responses, and from computational strategies to developmental considerations. Through an in-depth exploration of these diverse facets of stress assessment, our literature review establishes a solid groundwork for our research, steering our investigation towards innovative strategies and interventions in the domain of stress management.

Cohen et al. developed a widely utilized measure of perceived stress, involving self-reporting on overall stress levels [5]. Masuda et al. devised the Social Readjustment Rating Scale to quantify stress based on significant life events [6]. Lovibond et al. introduced the Depression Anxiety Stress Scales to assess emotional states related to stress [7]. These subjective assessment tools encompass various dimensions of stress experiences, including cognitive, emotional, and behavioral aspects [8].

Researchers present a biologically inspired model for optimal fear detection through facial expression analysis. Utilizing a four-layer computational approach, the model demonstrates superior performance [8].The research by Uddin et al. [9] focuses on identifying human stress levels in industrial workers using electroencephalogram (EEG) signals. Using a hybrid feature analysis and a two-layered autoencoder neural network; achieves stress detection. The work introduced a novel multimodal hierarchical weighted framework for detecting emotional distress vocal, and verbal cues. The framework uses residual networks and CNNs for facial cues, LSTM and CNN for audio, and a BERT transformer for text [10].

Physiological signals offer objective measures of stress responses. McEwen et al. discussed the physiology and neurobiology of stress, emphasizing the brain's role in stress responses [11]. Chrousos et al. focused on stress system dysregulation leading to stress-related disorders [12]. Kivimäki et al. conducted a meta-analysis linking work stress to cardiovascular disease, demonstrating the physiological impact of chronic stress [13]. The Task Force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology established heart rate variability standards, a physiological stress marker [14]. Thayer et al. proposed a neurovisceral integration model explaining how the autonomic nervous system regulates emotions and physiological responses to stress [15].

Machine learning algorithms are vital for classifying stress using physiological data. Jain et al. reviewed statistical pattern recognition techniques forming the basis of many machine learning algorithms [16].

Feature extraction and selection are crucial for identifying patterns in physiological stress data. Guyon et al. introduced variable and feature selection methods like filter, wrapper, and embedded approaches [17]. Uddin Chandrashekar et al. surveyed feature selection methods, comparing them based on computational complexity and effectiveness in stress research [18]. Saeys et al. reviewed feature selection techniques in bioinformatics, applicable to physiological data analysis in stress research [19].

Charles et al. reviewed social and emotional ageing processes, highlighting age-related changes in stress reactivity and regulation [20]. Ohal et al. in previous work have explored other physiological signal - to detect the stress from the signal slowing characteristics of electroencephalogram signals [21].

3- Proposed Methodology

This research paper introduces a methodology for stress detection by amalgamating subjective assessments via questionnaires and physiological data acquired through a photoplethysmogram (PPG) sensor. The objective is to enhance stress detection accuracy by customizing the data collection process for distinct age groups. The proposed methodology encompasses participant consent, age-specific questionnaire administration, pulse data collection utilizing an IR sensor, and subsequent data processing and analysis employing machine learning algorithms such as SVM and KNN. The system architecture, illustrated in the accompanying figure 3, demonstrates the sequence of data flow and processing stages integral to the proposed methodology.

This architectural depiction elucidates the integration and processing of subjective assessments alongside physiological data to achieve precise stress level detection.

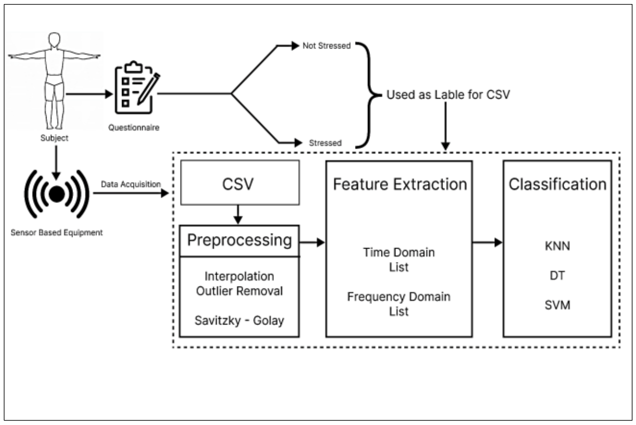

Figure 3. System Architecture Diagram

Stress is a pervasive health concern impacting individuals across diverse age groups. This research aims to construct an effective stress detection system by integrating subjective responses and physiological data, specifically, pulse data obtained through a PPG sensor [22].

3-1- Questionnaire Design

While designing the questionnaire, authors have consulted the psychologist, therapist as well as a few research papers which gave a thoughtful insight for the questionnaire design [23], [24], [25] . The Age-Specific Questionnaire: Devise and administer a questionnaire tailored to different age groups to gather subjective stress assessments. The questionnaire seeks to capture varied perspectives on stress experiences among participants. The questionnaire comprises 40 questions aimed at gauging levels of test anxiety. The questionnaire aims to assess the prevalence and impact of test anxiety across various aspects of an individual's academic and personal life. It consists of 40 questions divided into different categories, covering aspects such as the frequency of test anxiety experiences, coping mechanisms, academic performance, and overall well-being.

A detailed overview of the questionnaire, including its categories and sample questions, is provided in Table 1.

Table 1. Overview of Questionnaire

Category	Sample Questions
Frequency of Test Anxiety	a. Do you encounter feelings of fear, anxiety, or helplessness before or during an examination? b. Do you often experience a sense of dread or impending doom before a test?
Impact on Academic Performance	a. Have you performed poorly on a test in the past and fear of repeating the Performance? b. Does your test anxiety affect your overall academic or career goals?
Coping Mechanisms	a. Have you tried relaxation techniques or mindfulness practices to cope with test anxiety? b. Do you frequently compare your abilities to others when preparing for a test?
Physical Symptoms and Health Impact	a. Do you feel nauseous, sweaty, or experience a rapid heartbeat, shortness of breath, or dizziness during an examination? b. Are you concerned that your test anxiety may negatively impact your long-term memory recall during exams?
Social and Emotional Impact	a. Do you feel embarrassed or ashamed when discussing test anxiety with others? b. Have you experienced a decrease in self-esteem due to test-related stress?
Behavioral Patterns	a. Have you ever resorted to cheating or unethical behavior during a test due to extreme test anxiety? b. Are you concerned that your test anxiety may negatively impact your future career opportunities for advancement?

3-2- Questionnaire Data Collection

Participant Consent: Obtain informed consent from participants, clearly explaining the study's objectives, data collection techniques, and confidentiality protocols. Stress the voluntary nature of participation and the freedom to withdraw at any point.

While collecting data, age, gender and occupation is asked to the participants.

3-3- Questionnaire Responses

a. Participants are required to indicate the frequency of experiencing various symptoms or behaviors associated with test anxiety using a scale ranging from 'Never' to 'Very Often'.
b. This scoring system in Table 2 quantifies test anxiety levels, aiding in a thorough analysis of stress experiences among participants from diverse age groups.
c. The responses received for this questionnaire clearly show that for the same situation different reactions/ responses are there, which proves the theory behind stress.

Table 2. Details of Scoring based on Categories

Response	Scoring points
Never & 'Rarely	Combined, these responses equate to 0 points.
Sometimes	This response amounts to 1 point
Often' & 'Very Often	Combined, these responses equate to 2 points.

Based on the total score derived from the responses, individuals can be classified into three groups:

a. Not Stressed: A score below 15 suggests that the individual is not experiencing significant levels of test anxiety and can proceed with their activities calmly.
b. Mild to Moderate Stress: Falling between 15 and 30, this score indicates a moderate level of test anxiety. Though not severely affected, the individual may benefit from practicing relaxation techniques and stress management strategies.
c. High Stress, Guidance Required: A score exceeding 30 indicates high levels of test anxiety, necessitating guidance and intervention to address the substantial impact of stress on the individual's well-being and academic performance. Figure 4 describes the strategy used to identify the stress level.

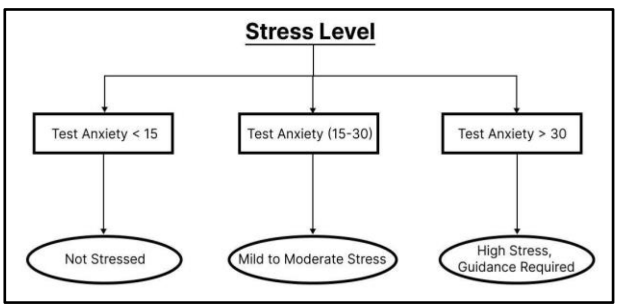

Figure 4. Stress level identification and label generation

The labels for the pulse data csv are generated from the questionnaire responses. These labels are not stressed, moderately stressed, and highly stressed. "High Stress, Guidance Required" for individuals with test anxiety scores surpassing 30, "Mild to Moderate Stress" for scores between 15 to 30 and "Not Stressed" for scores of 15 or below. This process allows the decision tree to categorize participants into various stress levels based on their test anxiety scores, offering a clear visual depiction of the decision-making process and facilitating comprehension of how data is categorized. By analyzing the responses and tallying the total score, individuals can gain insight into their level of test anxiety and take appropriate measures to manage it effectively[26] [27].

3-4- Wrist Pulse Data Collection

Many researchers have tried guessing the stress level using wearable devices. In these devices the sensors are the most important part [28], [29].

a. PPG Sensor Placement: Proper placement of the Photoplethysmography (PPG) sensor underneath the wrist is vital for precise pulse data acquisition. This sensor functions by detecting alterations in blood volume through the emission of light into the skin and subsequent measurement of the reflected or transmitted light. Focusing on the artery, commonly the radial artery located in the wrist, guarantees accurate measurement of pulse rate and waveform attributes [30]. For visual guidance on sensor placement, please refer to Figure. 5.

Figure 5. PPG Sensor Placement on Wrist

b. Pulse Data Collection: After positioning the PPG sensor correctly, it continuously monitors variations in blood volume linked to each heartbeat. Subsequently, these measurements are captured at consistent intervals and archived in a CSV (Comma-Separated Values) file format. Each entry within the CSV file usually includes a time-series dataset alongside the corresponding pulse rate value, thereby constructing a time-series dataset suitable for subsequent analysis [31].

3-5- Data Preprocessing

a. Interpolation: To handle missing or irregularly sampled pulse data points, interpolation techniques are utilized. These gaps may occur due to sensor malfunctions, motion artefacts, or technical glitches. Interpolation methods like linear or spline interpolation estimate the absent values by considering adjacent data points, thereby ensuring a continuous and evenly sampled dataset suitable for analysis.
b. Savitzky-Golay Filter: The application of the Savitzky-Golay filter aims to smooth and remove noise from the pulse data. Known for its effectiveness in eliminating high-frequency noise while retaining essential signal features like the underlying pulse waveform, this filter enhances data quality by reducing artifacts. Consequently, the accuracy of subsequent analytical procedures is improved [32]. For a visual representation of the data before and after preprocessing, please refer

to Figure. 6. This graph represents the filtered data for subject 1. After applying the this filter, the data becomes smoother, with reduced noise while preserving key features like peaks and edges. This Savitzky-Golay filter also has maintained the shape and height of signals as shown in graph of Figure 6.

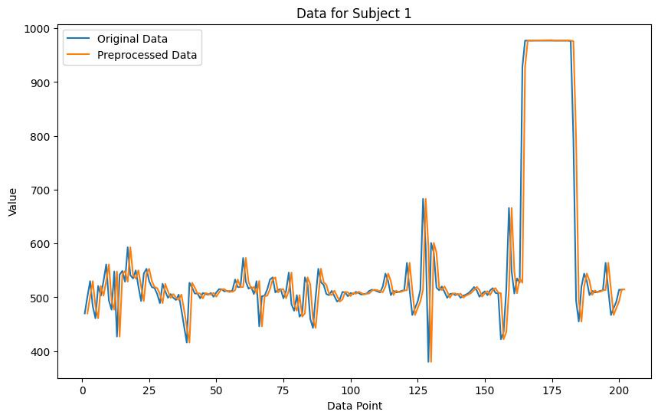

Figure 6. Graph of Original & Pre-processed Data

3-6- Feature Extraction

Time Domain Features: Time domain analysis entails examining signal characteristics along the time axis. In pulse signal analysis, these features offer insights into the temporal aspects of the heartbeat waveform, directly derived from pulse data. These features encompass metrics like average pulse rate, variance, median, maximum and minimum values, range, and Root Mean Square of Successive Differences (RMSSD). They offer an understanding of the overall characteristics of the pulse signal, depicting alterations in heart rate and variability across time.

List of Features Extracted:

a. Average Pulse Rate: The mean of pulse intervals over a specific time, indicating heart rate centrality.
b. Variance: Measures pulse interval dispersion around the mean, reflecting heart rate variability.
c. Median: The middle value of pulse intervals, providing a robust centrality measure.
d. Maximum and Minimum Values: Identifies peak and trough pulse intervals, showing heart rate fluctuation range.
e. Range: Difference between maximum and minimum pulse intervals, indicating overall heart rate variation.
f. Root Mean Square of Successive Differences (RMSSD): Quantifies variation in successive pulse intervals, reflecting short-term heart rate variability.

Frequency Domain Features: Frequency domain analysis examines signal frequency components and distribution. In pulse signal analysis, these features reveal heart rate variability's spectral characteristics, reflecting autonomic nervous system activity [33].

Frequency domain features are calculated to assess the spectral attributes of the pulse signal. These features encompass details concerning the energy distribution across various frequency bands, encompassing metrics of heart rate variability (HRV). The analysis in the frequency domain offers an understanding of the activity of the autonomic nervous system and can unveil patterns linked with stress and physiological arousal [34].

List of Features Extracted:

a. Power Spectral Density (PSD): Estimation via Fast Fourier Transform (FFT) or Autoregressive (AR) modelling decomposes pulse signals into frequency bands (VLF, LF, HF).
b. Total Power: Overall power across frequency bands, reflecting heart rate variability.
c. LF/ HF Ratio: Ratio of LF band power to HF band power, indicating sympathovagal balance.
d. Normalized LF and HF Power: LF and HF power in normalized units, facilitating comparison across individuals or conditions.
e. Peak Frequency: Identifies the spectrum's highest power frequency, showing the dominant heart rate oscillatory component.

Integrating time and frequency domain features offers a comprehensive understanding of heart rate dynamics under various conditions. These serve as valuable markers for assessing cardiovascular health, stress responses, and autonomic nervous system function[35].
For a visual representation of the Plot of Selected Features please refer to Figure 7.

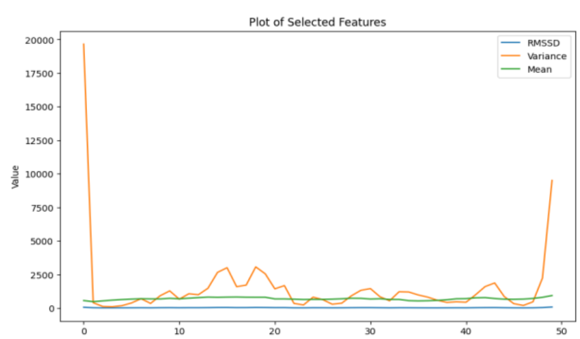

Figure 7. Plot of Selected Features

3-7- Feature Selection

During the feature selection phase, the aim is to pinpoint the most pertinent and informative features crucial for stress detection from the pool of extracted features.
This entails scrutinizing the correlation among features, evaluating their discriminative capability, and cherry-picking a subset of features that effectively distinguish between stress and non-stress scenarios. This approach aids in curtailing dimensionality and computational intricacies, thereby bolstering the efficacy of the classification model [35].

3-8- Labeling the data

The pulse feature data of every subject is stored in the CSV format. The data is then labeled as per the result obtained during the questionnaire responses stage. These labels are not stressed, moderately stressed, and highly stressed.
Summarizing the proposed methodology, emphasizing its potential for accurate stress detection by integrating subjective assessments with physiological data. Highlighting the significance of the age-specific approach in improving system performance. This proposed methodology establishes the groundwork for a comprehensive stress detection system, combining subjective and physiological data collection, preprocessing, feature extraction, feature selection, and classification methodologies to establish a comprehensive framework for a nuanced understanding of stress across various age groups. By harnessing sophisticated analytical techniques and machine learning algorithms, this approach furnishes a robust and precise mechanism for identifying stress patterns from physiological signals

4- Result and Discussion

4-1- Classification Techniques

1. Support Vector Machine (SVM): The Support Vector Machine (SVM) stands as a supervised learning technique employed for classification purposes. Concerning stress detection, SVM scrutinizes the chosen features and creates a hyperplane that segregates stress and non-stress occurrences within the feature space. The objective of SVM is to widen the margin between diverse classes while mitigating classification errors, thus furnishing a sturdy and efficient approach for stress classification [36].

2. k-Nearest Neighbors (KNN): The k-Nearest Neighbors (KNN) algorithm is a non-parametric classification method that categorizes instances based on their resemblance to nearby data points. In stress detection applications, KNN assesses the proximity of a specific instance to its closest Neighbors within the feature space and assigns it to the predominant class among those Neighbors. Renowned for its simplicity and adaptability, KNN is well-suited for various classification tasks, including stress detection [37] [38].

3. Decision Trees (DT): The Decision Tree (DT) is a robust classification method that divides the feature space into smaller regions, each corresponding to a specific class label. Their transparency in decision-making is particularly advantageous in domains like healthcare and finance. DTs can effectively handle both numerical and categorical data without extensive preprocessing and can capture nonlinear relationships. However, they are prone to overfitting, which can be addressed through techniques such as pruning or ensemble methods. In summary, DTs offer a valuable combination of simplicity, interpretability, and performance, making them a useful tool in various classification tasks, including stress detection [39].

4-2- Results

The methodology proposed for stress identification, which integrates subjective self-report data and objective physiological signals, has yielded promising outcomes. After data collection, preprocessing, feature extraction, and classification using machine learning algorithms, the accuracy of stress level classification was evaluated. For a visual representation of the data for Normal & Stressed Subjects, please refer to Figure. 8.
The Support Vector Machine (SVM) classifier achieved an accuracy of 0.98 with a standard deviation of ±0.20, indicating precise identification of stress levels. Moreover, the Decision Tree classifier attained an accuracy of 0.93 (±0.30), while the K-Nearest Neighbors (KNN) algorithm demonstrated an accuracy of 0.88 (±0.44). Table 3 demonstrates the accuracy of these classifiers. These results underscore the effectiveness of the proposed methodology in accurately classifying stress levels based on both subjective and physiological data.
The high accuracy levels achieved by the SVM classifier underscore the robustness of the proposed methodology in stress identification. SVM's capability to establish a hyperplane effectively separating stress and non-stress instances within the feature space contributes to its superior performance. Though slightly less accurate, the decision tree classifier provides an intuitive representation of the decision-making process, aiding in the interpretation of stress classification outcomes.

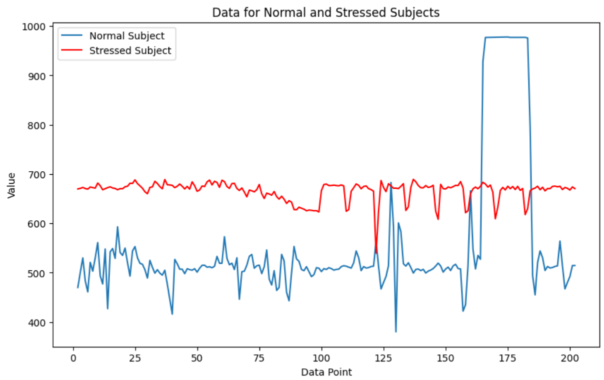

Figure 8. Graph of Data for Normal & Stressed Subjects

Table 3. Classifier accuracy

Classifier	Accuracy
SVM	0.98 (+/- 0.20)
Decision Tree	0.93 (+/- 0.30)
KNN	0.88 (+/- 0.44)
Voting Classifier	0.986

In this study, a Voting Classifier was employed to enhance stress detection accuracy by combining SVM, decision tree and KNN machine learning models. The classifier aggregated predictions using both hard voting and soft voting techniques, leveraging the strengths of individual models. Experimental results demonstrated that the Voting Classifier outperformed individual classifiers, achieving improved accuracy of 98.6 %.

The existing work of researchers have been discussed in upcoming paragraph and have been listed in Table 4.

Table 4. Comparison with Existing Work

Author	Method	Performance
Awasthi et al [36]	SVM	86%
Awasthi et al [36]	Decision tree	82%
Kim et al [38]	K-means clustering	87%
Proposed	Voting classifier	98.6%

Awasthi et al [36], have trained SVM and decision tree as machine learning models for classification of stress and classified it as high stress vs average stress. This work has explored and used Pulse Rate Variability (PRV) as features to classify the stress and have achieved the accuracy of 86% and 82% respectively. The work of Kim et al [38] have experimented for the number of clusters to use for classification of stress using elbow method and have come to with optimal value of k as 12. This research work after SVM, KNN and decision tree have implemented Voting classifier to achieve the improved the results of 98.6% of accuracy.

The integration of subjective self-report data, acquired through tailored questionnaires, with objective physiological signals enhances the comprehensiveness and accuracy of stress assessment. By capturing both cognitive and physiological responses to stressors, the proposed methodology offers a holistic understanding of individuals' stress experiences.

The age-specific approach in questionnaire design acknowledges the diverse manifestations of stress across different life stages, thereby improving the relevance and accuracy of stress assessment. Additionally, the utilization of physiological signals, such as pulse data obtained through infrared sensors, adds an objective dimension to stress detection, reducing reliance on self-reported data alone.

The findings of this study have significant implications for various fields, including healthcare, psychology, and human-computer interaction. By providing a nuanced understanding of stress dynamics and effective stress detection mechanisms, the proposed methodology can inform the development of tailored interventions and support systems for individuals experiencing stress.

However, it's important to acknowledge some limitations of the study. The sample size and demographic diversity of the participants may impact the generalizability of the results. Further research is necessary to validate the proposed methodology across different populations and settings.

In conclusion, the integration of subjective and physiological data through machine learning techniques offers a promising approach to stress identification. By leveraging the strengths of both subjective and objective measures, the proposed methodology contributes to advancing the field of stress management and well-being.

The future work of this research is to enhance machine learning algorithms, so that the accuracy and reliability of stress detection from PPG signals can be significantly improved. Additionally, combining PPG data with other physiological signals, like ECG and GSR, can provide a more comprehensive understanding of stress. The work can be integrated further into personalized stress management applications and clinical applications of PPG sensors that can aid in the early detection and management of stress-related health issues, contributing to better healthcare outcomes.

5- Conclusion

Acknowledging the extensive research presented in this paper, it's evident that the work represents a significant advancement in stress identification methodologies. The integration of subjective self-report data with objective physiological signals, supported by machine learning techniques, provides a nuanced and comprehensive approach to stress assessment. This multifaceted methodology holds significant promise across various domains such as healthcare, psychology, and human-computer interaction.

In conclusion, this research paper introduces an innovative framework for stress detection that addresses the urgent need for precise and reliable assessment tools in today's dynamic environments. By tailoring questionnaires to different age groups and pairing them with sophisticated physiological data collection methods, the proposed methodology enables a holistic understanding of stress experiences. The integration of advanced machine learning algorithms further enhances the accuracy and effectiveness of stress identification, representing a significant advancement in the field.

This study not only contributes to advancing our understanding of stress but also emphasizes the importance of adopting multidimensional approaches for comprehensive assessment and intervention strategies. By combining subjective insights with objective physiological measurements, the proposed framework offers unprecedented depth and detail in stress assessment. Additionally, the technical rigor demonstrated in data preprocessing, feature extraction, and classification techniques highlights the robustness and reliability of the proposed methodology.

Looking forward, this research lays a solid foundation for further exploration and application in real-world contexts. As stress continues to impact individuals' well-being across diverse demographics, the integration of subjective and objective measures is poised to transform stress management and prevention strategies. By leveraging state-of-the-art technologies and methodologies, this study not only advances current research but also holds significant potential for practical implementations to improve mental health and overall quality of life.

In summary, this research represents a groundbreaking contribution to the field of stress identification, offering a sophisticated and scientifically validated methodology that promises to reshape our understanding and management of stress in contemporary society.

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Acknowledgments

We, the authors, want to acknowledge the efforts made by a few medical practitioners, who helped us a lot in understanding stress-related issues. We also thanks to researchers whom we referred while writing the paper.

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Journal of Information Systems and Telecommunication
Vol.13, No.2, April-June 2025, 122-129

http://jist.acecr.org
ISSN 2322-1437 / EISSN:2345-2773

Transmission Parameter-based Demodulation in Visible Light Communications using Deep Learning

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Received: 18 Jul 2024/ Revised: 04 May 2025/ Accepted: 26 May 2025

Abstract

This paper proposes an innovative approach by employing a one-dimensional Convolutional Neural Network (CNN) for demodulation in VLC systems. The used Data-set is real and available online, providing a robust foundation for analysis. It encompasses modulated signals in seven different modulation types, with 29 transmission distances ranging from 0 to 140 centimeters. By accounting for the varying distances between the transmitter and receiver, the model can more accurately interpret the received signals. Additionally, the study suggests that utilizing memory to learn previous symbols, which is essential for mitigating the effects of inter-symbol interference (ISI), can significantly improve demodulation accuracy. Our results of memory-based demodulation show a better performance in contrast to the previous one (AdaBoost).

Keywords: Demodulation; VLC; Distances; Convolutional Neural Network; ISI.

1- Introduction

Today, due to the fast development of electronic and digital devices, we are facing a familiar problem called the increase of wireless data traffic. One of the solutions is fast wireless transmission [1][2]. Visible Light Communication (VLC), due to its advantages such as unregulated spectrum, excellent security, and stability to electromagnetic interference, has been considered by researchers in the field of short-range fast wireless communications [3].

The accurate positioning is difficult in indoor optical communication scenarios [4]. There are several indoor positioning technologies to achieve the desired result, such as Global Positioning System (GPS), infrared, Ultra-Wideband (UWB), ultrasonic, etc. Although these technologies have high accuracy in positioning, most require specialized infrastructure that leads to high costs [5]. Other cases of indoor positioning, such as radio frequency identification (RFID) and Wi-Fi, can be affected by mutual interference and multi-path effects; therefore, high-accuracy positioning cannot be achieved. Recently, indoor positioning has been accepted as a promising candidate in VLC [6]. To achieve better positioning performance, the machine learning (ML) method can be introduced in indoor positioning with VLC [7].

ML-based model-free demodulators are becoming popular, where the need for prior knowledge can be eliminated. In the modulation process, the phase and amplitude of the signals are modulated [8]. Recently, much work has been done in VLC applications using ML, and we will review some of them. Ma et al. [9] studied three types of demodulators based on ML methods in VLC, including eight modulation types. Their proposed convolutional neural network (CNN) model receives images generated using the modulated signals and recognizes the signal by image classification. In [10], they proposed a semi-supervised self-trained large margin classifier to track and classify popular single carrier modulations in nonstationary environments, demonstrating robust performance even in low SNRs. In [11], K. Majeed et al. have done comprehensive research on indoor positioning for VLC, in which the combination of multiple classifiers, including KNN, RF, and ELM, was studied. They have shown that by increasing the distance, the positioning accuracy decreases. Lin et al. [12] proposed the CNN in the NOMA-VLC system, in which signal compensation and retrieval are performed jointly, which can improve the distortion caused by multi-directional scattering. Shi et al. [13] presented ML-based techniques for communication signal demodulation. These techniques are used in channel estimation and traditional decision-makers.

In [6], demodulation is used for carrier-less amplitude-phase (CAP) modulation, which is a significant modulation. Also, criteria such as accuracy, bit error ratio (BER), and signal-to-noise ratio (SNR) have been investigated; experimental results show that CAP- VLC-based systems

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result in better performance, including 92.4 % accuracy in various conditions and increased BER. In [14], M-QAM (M = 16, 32, 64, 128, 256), OOK, QPSK, 4-PPM, modulation schemes have been investigated, and in addition, two DL-based demodulators and AdaBoost have been proposed.
However, in [9], the images are used as data, and the demodulation accuracy is not high and acceptable; also, in [11] [12], the complexity is high, and the accuracy is low due to the use of multiple classifiers for positioning. The disadvantages of [13] and [10] are that the demodulation accuracy depends on SNR, and the distance is not considered.
In this paper, for the first time, we have applied distance information in signal demodulation; therefore, the network can learn and benefit from it to increase signal demodulation accuracy. Joint demodulation and ranging are performed using 1D-CNN, in which the signal sequence is considered the network input. The sequence is a one-dimensional input that needs a simpler network than the neural networks, which take the images as input data. Moreover, real VLC data with 29 different distances and seven modulation types are used to evaluate the performance of the proposed method.
In the proposed network, each label is equivalent to a modulation level and its distance, and by classifying a symbol, demodulation and its distance are determined. This dual capability significantly streamlines the process, making it more efficient and accurate.
The proposed 1D-CNN can increase the demodulation accuracy by applying memory and distance information, specifically for higher-order modulations and long distances. This is particularly important in VLC systems, where signal degradation can be significant at greater distances and higher modulation orders. The inclusion of memory helps the network to understand the signal context better, improving its ability to demodulate accurately. Furthermore, our method simplifies the network design while maintaining high performance, making it a practical solution for real-world VLC applications.
Additionally, we explored various configurations of the network to optimize its performance. By adjusting parameters such as the length of the input sequence and the depth of the network, we were able to find the best settings that maximize accuracy. The results from our extensive simulations show that our approach not only outperforms traditional methods but also offers a robust solution that can adapt to different environmental conditions and modulation schemes.
Integrating of distance information and memory into the 1D-CNN represents a significant advancement in the field of VLC. This approach increases demodulation accuracy and provides a comprehensive framework for addressing common challenges in optical wireless communications. The use of real-world data further validates the effectiveness of our method, demonstrating its potential for deployment in practical scenarios. Future work could expand on this foundation by exploring additional ways to leverage contextual information and improve network architecture, paving the way for even more sophisticated and reliable VLC systems.

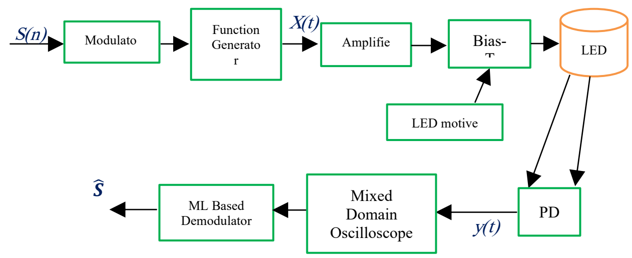

Fig 1: Demodulation based on ML of VLC [9].

2- Methodology

The system model used in this study is identical to that of [9], which is briefly illustrated in Fig. 1. For more detailed information, please refer to [9].

2-1- Data-set

The used data set generated in real physical environments is accessible via https://pan.baidu.com/s/1rS143bEDaOTEiCneXE67dg [9] in seven modulation schemes: 16-QAM, 32-QAM, 64-QAM, 128-QAM, 256-QAM, OOK, and QPSK. 29 transmission distances ranging from 0 cm to 140 cm are considered for the seven modulated signals. There are four different numbers of sample points (N = 10, 20, 40, 80) in each period for every modulation scheme. Lengths of signals according to the total number of periods in each case are listed in Table 1.
It can be seen from Fig. 2 that all 16 labels of 16-QAM have no similarity in amplitude and phase.

2-2- Network Structure

Due to the simplicity and high efficiency of the CNN network, we used this type of network for demodulation. The distance information of the received signal is used for demodulation; the different distances can have specific features, such as SNR, which can help the demodulation process. Furthermore, it is important to note that the sequence of the received signal serves as the singular input for the network. By utilizing this one-dimensional input, a more straightforward neural network can be constructed compared to those designed for two- or three-dimensional images. This is due to the fact that signals represented in image form often contain extraneous and redundant information. The intricacies of the model put forth are delineated further in the subsequent discussion.

In this research, a series of signals is regarded as the fundamental input data for a demodulator rooted in Convolutional Neural Network technology. The dimensions of each input vector are inherently contingent upon the signal's specific sampling rate. Delving deeper into this discourse, the innovative CNN architecture being presented comprises four meticulously crafted convolutional layers, a pivotal Global Average Pooling layer, and two intricately designed fully-connected layers. These convolutional layers serve as vital components aimed at extracting imperative features from the input data by employing filters of varying sizes. Moreover, it is crucial to mention that the depth of these filters has been discerningly determined with precision based on the unique characteristics inherent within each individual convolution layer, thus encapsulating an intricate level of complexity as delineated in.Eq. (1):

$$y_k^l = b_k^l + \sum_{i=1}^{N_{l-1}} w_{ik}^l * x_i^{l-1} \qquad (1)$$

Where y_k^l and b_k^l denote the *k-th* feature map and its bias in layer l, x_i^{l-1} is the *i-th* feature map in layer *l-1*, w_{ik}^l is the weights from *i-th* feature map in layer *l-1* to the *k-th* feature map in layer l, (*) represents the convolution operator and N_{l-1} is the number of feature map in layer *l-1* [15].

The Global average pooling layer reduces the number of parameters that can be trained during model learning [16] [17]. In the realm of Classification, SoftMax activation performs two classes in the fully connected layer. As mentioned, these two types each represent two parameters; The estimated distance and the desired modulation symbol number will result in 29*L classes, where L is the number of desired modulation labels. For example, we have 29*32 classes in 32-QAM. Each class is related to a modulation label and its distance. At this layer, the learning method uses feed-forward and back-propagation algorithms [18].

The Leaky RELU is applied as the activation function for all convolutional layers, and in the last layer, the SoftMax function is used. In the RELU activator function, some neurons die or become inactive, and the output becomes zero. To solve this issue, a function called Leaky RELU is used, which prevents the death of neurons with negative values. In our proposed CNN, the Leaky ReLU activation function is employed instead of the standard ReLU. While ReLU is widely used due to its simplicity and effectiveness in mitigating vanishing gradients, it suffers from the "dying ReLU" problem, where some neurons output zero for all inputs and stop learning during training. To address this, Leaky ReLU introduces a slight negative slope (e.g., 0.1x) for inputs less than zero, ensuring that all neurons propagate gradients during backpropagation. This modification enhances the model's learning capability and stability, especially in deep architectures. The choice of Leaky ReLU is based on empirical tests, which showed more consistent convergence and slightly improved accuracy compared to standard ReLU. The Leaky RELU formula is according to Eq. (2):

$$f(x) = \max(0.1x.x) \qquad (2)$$

The SoftMax function calculates the probability associated with each output, and this type of function is used in the last layer of the network and gives the output probability. So, the sum of the probabilities = 1 [9]. The SoftMax formula is based on Eq. (3):

$$softmax\,(z_i) = \frac{\exp\,(z_i)}{\sum_{j=1}^{K} \exp\,(z_j)} \qquad (3)$$

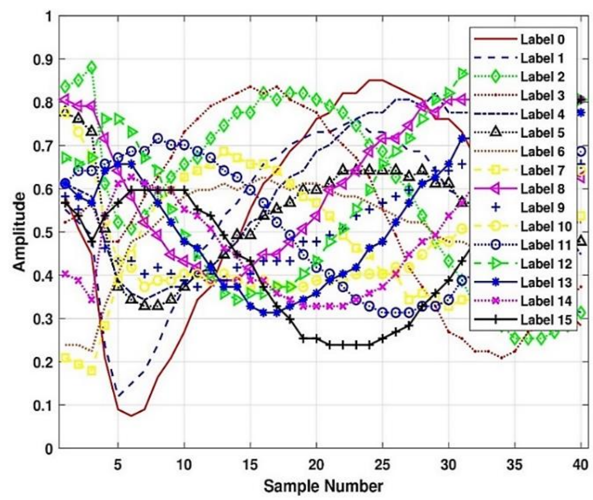

Fig 2: Some samples of 16-QAM signal

The structure of the proposed network is shown in Fig. 3, and the details of the proposed model are described in Table 2. The input signal is fed to the Conv-1 layer with 38 filters, generating 38 feature maps; then, Batch-Normalization is utilized. The same operations are applied to all four layers but with different filter sizes and numbers. Finally, the Global average pooling layer is connected to the fully connected layer. The multi-path propagation channel is one of the main challenges in indoor OWC. A reflected signal will have a slight delay and reduce all signal levels except the LOS links. However, the signal reaches the Rx through different paths, with various delays and attenuation.

In this paper, we add memory to the CNN network to increase the accuracy and efficiency of the system for demodulation and distance estimation. We propose to employ the information of previous symbols on the current signal by adding them to the input signal sequence.

Finally, we randomly separate 70% of the training data, 20% for test data, and 10% for validation data.

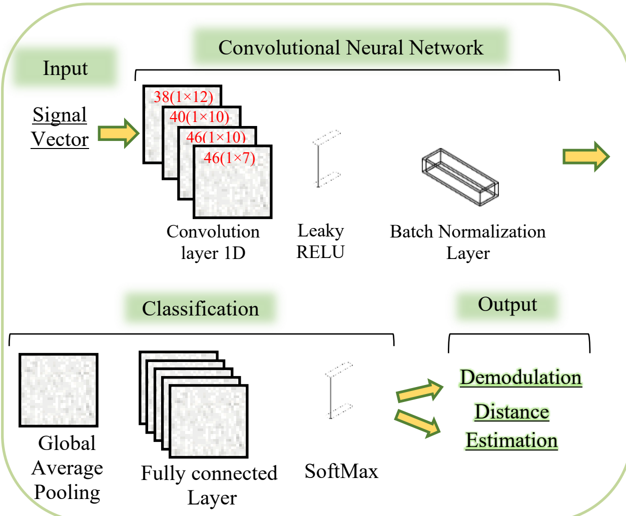

Fig 3: The structure of the proposed network

2-3- Performance Evaluation and Implementation Detail

In this paper, we have performed demodulation and distance estimation for M-QAM (M = 4, 16, 32, 64, 128, 256) and OOK modulations at 0 to 140 cm (for 29 distances). The proposed CNN was implemented for four different values of N = 10, 20, 40, and 80, where N represents the number of signal samples in each period. In this experiment, the batch size is set to 3500, the epoch number ranges from 100 to 200, and the Adam method is used as the optimizer. The network measurement criterion for this work is the accuracy of demodulation. All the proposed methods are implemented with MATLAB R2021b and executed on a computer with an Intel Core i7-4200 CPU @ 1 GHz/8GB RAM.

The choice of these specific parameters was made after extensive experimentation to ensure optimal network performance. Varying values of N allowed us to observe how the number of signal samples affects demodulation accuracy, providing insights into the optimal configuration. The batch size of 3500 ensured efficient training, and the range of epochs (100 to 200) balanced training time with performance, preventing overfitting.

The Adam optimizer facilitated fast and stable convergence, handling sparse gradients and adaptive learning rates effectively. Despite the modest computational setup, the Intel Core i7-4200 CPU and 8GB of RAM were sufficient for training and testing the CNN.

Supplementary tests, including varying modulation schemes and distances, adjusting batch sizes, and experimenting with optimizers, reinforced our findings

3- Discussion and Results

Table 2: The parameters of the CNN

Layers	*Filter Size*	*Number of Filters*
Conv-1	1×12	38
Conv-2	1×10	40
Conv-3	1×10	46
Conv-4	1×7	46

3-1- Discussion

We have to specify that for demodulation and distance estimation, we used real normalized data provided by [9]. In the data, d is the distance between the LED and PD, and it is collected every 5 cm from d = 0 cm to d = 140 cm and normalized. This data-set can be helpful for commenting on examples of how approaches perform under various circumstances. Nonetheless, there are still many research topics left to be explored in the VLC system, more specifically, concerning the channel modeling. Performance can be enhanced when the system is designed to incorporate selected machine learning (ML). Therefore, using DL, and specifically, the CNN architecture, we succeeded in demodulating seven different modulations, among which M-QAM (M = 4, 16, 32, 64, 128, 256), and OOK in VLC.

The simulations were carried out in MATLAB; first, distance was estimated, and then demodulation was done. In order to increase the experiment accuracy, we used memory in the CNN for the previous symbols that influenced the current symbol. First, the network was trained for 32-QAM with a lesser distance using 1D-CNN to design the basic classifier. Optimum demodulation accuracy of the transmitted information was obtained by fine-tuning of the various network parameters. This approach aimed to extend the length of the 1D input sequence where two previous signals are added to the current one, making the input 3-channels (3-ch).

To analyze the effect of changes in memory and size of the input sequence, we trained the proposed network with the 5-ch, 8-ch, 10-ch, and 12-ch input data arrangements. It is worth noting that although explicit experiments with controlled SNR values were not conducted, the data-set inherently reflects a range of SNR conditions through the variation of transmission distances. As distance increases from 0 cm to 140 cm, the received signal power decreases, effectively reducing the SNR. Also, the data-set is collected under real conditions. It is true that for different distances, SNR changes, but since the data-set is real, we do not have SNR. Last but not least, we examined modulation accuracy when the channel is specified with different parameters. In order to evaluate the correctness of the discussed CNN-based demodulation method considering 32-QAM modulation, the distance-dependent results are shown in Fig. 4 for different values of N = 10, 20, 40, 80. This analysis likewise shows a clear trend of the modulation accuracy for N = 40 outcompeting the others, hence supporting the conclusion of [9]. The choice of input sequence length N is crucial in balancing demodulation accuracy and real-time processing feasibility. While larger values of N (e.g., 40 or 80) capture more signal context and improve classification accuracy, they also increase the computational load and inference latency. In contrast, smaller N values (e.g., 10 or 20) are faster to process but yield lower accuracy, as shown in our comparative results. Therefore, N=40 was selected as a practical trade-off, offering reliable demodulation and acceptable complexity for real-time applications.

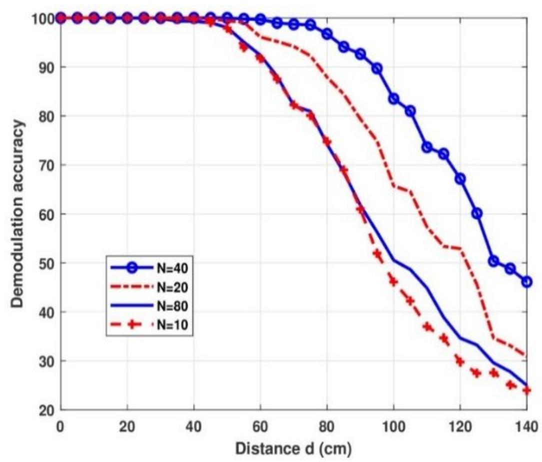

Fig 4: The demodulation accuracy of CNN versus distance *"d"* in diferent sample points.

Fig. 5 shows the demodulation accuracy of 32-QAM with distance relation in (d) for N=40 in order to assess the influence of memory on the performance. The accuracy is much higher when demodulating with more than one channel up to 10 channels (10-ch). Also, the probability for eradicating the virus is much higher in the early stage of its spreading. Coefficients for 32-QAM are N= 40, ch= 10; furthermore, experiments showed that. Therefore, the simulations are performed for N=40 and ch =10. The network training is illustrated based on the demodulation accuracy of the CNN demodulation method in Fig. 6.

Depicted below are the accuracy levels obtained for the 16-QAM as well as 32-QAM configurations of the classifiers; it is evident that there is better accuracy for the 16- QAM than the 32- QAM and after achieving a success rate of about 75 % after 150 epochs the models exhibit steady performance.

These results clearly will open the potential of the proposed CNN-based demodulation technique to improve the precision and dependability of VLC systems. It is also believed that in the future, one might investigate the usage of this method in other forms of modulation and more complicated systems and scenarios in OWCs.

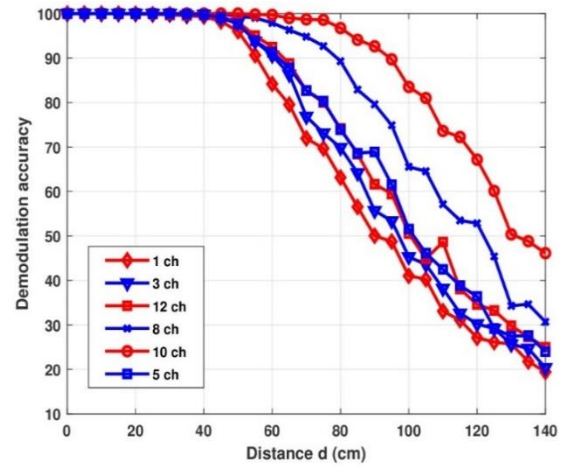

Fig 5: The demodulation accuracy of 32-QAM modulated signals versus distance d in: 1ch, 3 ch, 5 ch, 8 ch, 10 ch, 12 ch when N = 40.

To show the efficiency, it is necessary to explain that we tested different methods to reach the final result, which is reported in the article. Here, the main discussion is on the effect of memory and distance on demodulation accuracy; thus, we can have two types of networks besides the proposed method:

1. A network without any information from the last symbols.
2. A network where the distance effect is ignored.

This network demodulates only at one determined distance, and different networks are trained for each distance. In the first case, we have a regular and basic network, and the results are similar to the CNN-based demodulator referenced in [9]. Consequently, the accuracy is lower than that achieved by Adaboost, demonstrating the limitations of this approach when memory is not considered.

In the second case, the problem involves training a distance estimator before demodulation. This approach requires an additional step of accurately estimating the distance before demodulating the signal. The challenge here is that the error in distance estimation directly affects the symbol demodulation accuracy. If the distance estimator introduces errors, these errors will compound the demodulation error, leading to a significant degradation in performance. This method highlights the critical nature of accurate distance information in achieving high demodulation accuracy.

To further illustrate the benefits of the proposed method, we conducted extensive simulations comparing these network types with the proposed approach, which incorporates both memory and distance information. The results clearly showed that the proposed method outperforms the other two types of networks. By including the memory of previous symbols, our network effectively mitigates ISI, leading to higher accuracy. Additionally, considering the distance information, the network adapts better to varying conditions, further enhancing performance.

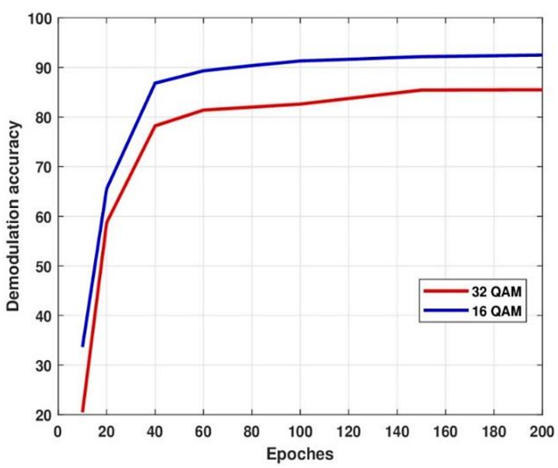

Fig 6: The demodulation accuracy of CNN based method with respect to epochs when N = 40 and 10 ch, d= all distance.

Moreover, we explored the effect of different memory lengths and how they influence the demodulation accuracy. Longer memory lengths generally led to better performance up to a certain point, beyond which the computational complexity increased without significant gains in accuracy. This finding suggests an optimal balance between memory length and computational efficiency, which is crucial for practical implementations.

Furthermore, the proposed method's robustness was tested across various modulation schemes and environmental conditions. It consistently demonstrated superior performance, underscoring its versatility and reliability. The comprehensive analysis and comparison provided in the article highlight the significant advancements made by incorporating memory and distance information into the demodulation process, paving the way for future research and development in this field.

In conclusion, our findings emphasize the importance of memory and distance information in achieving high demodulation accuracy in visible light communication systems. The proposed CNN-based approach substantially improves over traditional methods, providing a robust and efficient solution for practical VLC applications. Future work could focus on further optimizing the network parameters and exploring its application to even more complex scenarios, ensuring continued progress in this rapidly evolving field.

3-2- Results

From the results obtained, the demodulation accuracy reduces with the order of modulation and distance. In [9], the CNN, AdaBoost, DBN classifiers are employed to demodulation, and it is identified that AdaBoost was most accurate. A comparison between the proposed method and AdaBoost regarding demodulation accuracy is illustrated in Fig. 7. The analysis proves that improving accuracy can be achieved using information of distance and previous symbols. It is evident that at a distance of 140 cm, the augmentation in the accuracy can be over 50%. This is a big leap forward from the earlier procedures. The proposed network is extended to other modulations, and the results are shown in Fig. 8. As observed here, as the distance increases when employing higher-order modulation, the number of errors in the demodulation also increases.

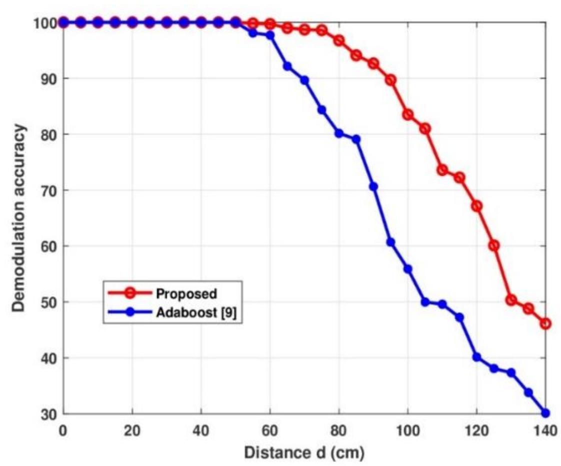

Fig 7: The demodulation accuracy of CNN based method for 32- QAM.

As shown in Fig. 8, the demodulation accuracy of the seven modulation schemes is inversely proportional to the distance d. Also, in M-QAM type systems, when the modulation level increases and for a fixed distance d, accuracy decreases even more. This indicates the difficulties encountered in ensuring high levels of accuracy of VLC systems with higher-order modulations and larger distances. This indicates that the proposed method can effectively address these problems by making use of distance and historical symbol information, which adds to the idea that the method can improve VLC system performance in real-world applications. This may be an area of interest where improved algorithms are sought for tackling more complicated problems and modulation types.

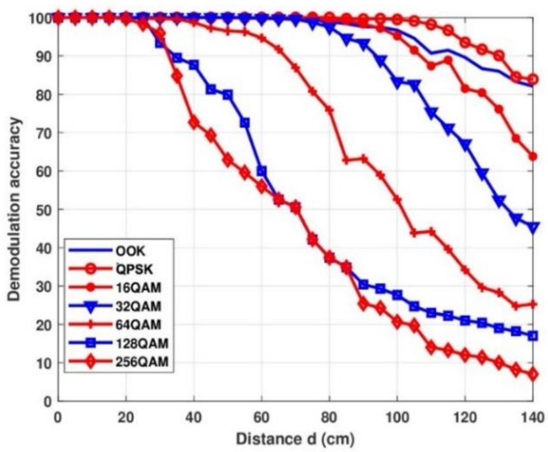

Fig 8: The demodulation accuracy of OOK, QPSK, 16-QAM, 32-QAM, 64-QAM, 128- QAM and 256-QAM modulated signals with respect to distance d when N = 40,10 ch.

4- Conclusions

TIn this research, the CNN was suggested in signal demodulation of VLC system that reveals its promising future. Testing the proposed method with a veritable dataset containing seven different modulations and 29 separate distances, the investigation of demodulation performance was quite accomplished. Other important parameters such as distance information were revealed to further improve the demodulation BER performance. Therefore, the number of inputs was chosen so that the network capacity was gradually adjusted to the best possible state.
Simulation results given in figures also showed that the proposed demodulator outperforms the existing conventional demodulator by a large margin. For example, at 140 cm distance the improvement for demodulating 32-QAM can go beyond 50%. This big advancement shows that integration of distance and historical symbol information into demodulation exercise is very efficient.
Moreover, analyzing the performance of the proposed CNN demodulator by applying it to different modulation schemes as well as distances, it can be concluded that improved performance is achieved. From these results, it can be concluded that the method is very flexible and, even when placed under extreme conditions, provides a high level of accuracy. However, it can be suggested that the future work could be done to investigate the further application of this approach to the more high-order modulation scenarios or the more complicated modulation environments. Furthermore, one can incorporate enhanced methods like learning rate adaptation and other advanced structures of the neural networks, which might result in further enhanced levels of demodulating efficiency. The findings of this particular study will illuminate other enhanced performances of the VLC system and will be helpful in improving such technologies as revealed in this research.

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Journal of Information Systems and Telecommunication
Vol.13, No.2, April-June 2025, 130-138
http://jist.acecr.org
ISSN 2322-1437 / EISSN:2345-2773

Designing a Hybrid Algorithm that Combines Deep Learning and PSO for Proactive Detection of Attacks in IoT Networks

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Received: 02 Nov 2024 /Revised: 03 Apr 2025/ Accepted: 04 May 2025

Abstract

As a result, with the establishment of Internet of Things (IoT) at a booming pace, the demand for effective, green security systems to detect cyber-attacks is escalating. Despite thorough investigation in this domain, the heterogeneous nature and multifaceted characteristic of IoT data make successful attack detection a challenging task. This paper introduces a new method for enhancing IoT attack detection through a hybrid deep learning model (CNN-GRU-LSTM) integrated with Particle Swarm Optimization (PSO) for hyperparameter optimization. This methodology consists of different steps, starting with a CSV (Comma Separated Values) file to use it as the dataset, performing different data science operations like feature selection, calculating weights to balance the class for learning the model, etc. A hybrid CNN-GRU-LSTM model is subsequently established and trained with the integration of the merit of each algorithm: CNN for spatial feature abstraction, GRU for effectiveness in managing the sequential information, and LSTM for discovering the long-range dependencies. The hyperparameters of the PSO algorithm are optimized to find the best combination of features/parameters to improve detection performance and efficiency. The results show remarkable accuracy and efficiency improvements over traditional methods. H. PSO for Optimizing Hybrid Deep Learning Architecture The gainful approach to building deep neural networks for IoT frameworks is through PSO based improvements. The results help to advance a realm of research work in IoT security and lay a grouped foundation for further work in optimizing attack detection models with different machine learning algorithms and optimization approaches.

Keywords: Deep Learning Algorithms; Internet of Things; IoT Attacks; PSO Algorithm.

1- Introduction

The rapid development within the field of the Internet of Things (IoT) has impacted diverse industries, fostering clever automation and seamless connectivity. However, these technological trends have also posted tremendous demanding situations, in particular in protection. The protection of IoT networks is essential for protective sensitive data and preserving the integrity of related devices [1].
This takes a look at ambitions to enhance protection mechanisms in IoT networks with the aid of developing superior strategies for attack detection. Given the substantial increase inside the quantity of IoT gadgets and their applications, the importance of locating robust and green safety solutions has grown. IoT devices regularly face computational resource constraints, which reduce the effectiveness of traditional protection answers. These limitations necessitate using modern tactics which are each green and powerful.
Significant advancements were made in IoT protection. The use of deep studying algorithms, in particular combinations like CNN-GRU-LSTM, has proven excessive capability in identifying complicated styles and anomalies in big datasets [2]. Despite these advancements, considerable gaps remain in contemporary studies, specifically in addressing the problem of records imbalance. This has a look at seeks a hybrid technique that leverages the strengths of various deep getting to know fashions to better capture complex IoT visitors' patterns. Additionally, characteristic choice optimization the usage of the Particle Swarm Optimization (PSO) set of rules is employed, which will help enhance the accuracy and performance of the model in detecting assaults inside imbalanced records.

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The number one goal of this research is to recommend a novel hybrid version for detecting assaults in Internet of Things (IoT) networks. This hybrid version, which integrates deep gaining knowledge of architectures consisting of CNN, GRU, and LSTM, is designed to enhance accuracy and performance in attack detection. Additionally, the Particle Swarm Optimization (PSO) set of rules is utilized for function choice optimization, helping in the effective management of problems springing up from statistics imbalance. The studies additionally compare the proposed version with present techniques like RNN, LSTM-RNN, GRU, and GRU-CNN to demonstrate the innovation and efficacy of the proposed version.

Research Contributions

This observe gives numerous tremendous contributions to the field of assault detection in IoT networks:

- Modeling Innovation: The advent of a hybrid version primarily based on CNN, GRU, and LSTM, which significantly improves the potential to locate complicated patterns and anomalies in IoT visitors.
- Hyperparameter Optimization: The use of PSO for feature selection optimization, which no longer best will increase detection accuracy however also reduces the computational complexity of the version. This technique is especially effective in addressing facts imbalance, enhancing the model’s efficiency in detecting rare but crucial assaults.
- Empirical Evaluation: A comprehensive assessment of the proposed model with current methods, providing empirical evidence of the proposed model's superiority and excessive efficiency, laying the foundation for the development of greater advanced protection systems within the IoT domain.

Organization of the Paper

- Section 2: Review of previous works in attack detection of IoT networks and deep learning techniques;
- Section 3: Proposed hybrid model is explained in detail with an elaboration of the process of feature optimization using PSO;
- Section 4: The Used datasets and preprocessing methods are explained;
- Section 5: Results of experiments with an illustration of the performance of the proposed model compared to existing methods.
- Section 6: Discussion and conclusion: This includes recommendations for possible future research.

2- Related Work

The current section is focused on research into IoT network attack detection, especially that related to deep learning algorithms applied within this domain. Original advanced approaches in machine learning and artificial intelligence aimed at raising the accuracy and efficiency of anomaly and cyber-attack detection in IoT environments are introduced and reviewed herein. The paper reviews recent research in comparison with older methods for these technologies that have impacts on increasing the detection power and reducing error rates in IoT networks.

In [3] reviews and compares some deep learning methods in intrusion detection in IoT devices. In this paper, different deep learning models were experimented with: Convolutional Neural Networks, Long Short-Term Memory networks, and Gated Recurrent Units. The results empirically show that these methods can be efficiently applied for attack detection in IoT environments. One of the main contributions of this research will be to introduce a proposed model for intrusion detection that will show high accuracy compared with the existing methods. In the methodology of this research, the implementation and evaluation of these models will be done using standard datasets for intrusion detection. It also discusses the limitations like extensive training data and a long training time for the models. It finally concludes that the deep learning models have some promise in improving attack detection, shows suggestions for future studies for classifying other variables, and improves the performance of the models.

In [4] deals with the investigation of a new model to detect attacks in the IoT environment. It applies deep learning techniques by proposing the combining scheme of optimization algorithms with Recurrent Convolutional Neural Networks to improve accuracy in detection. This paper offers two main contributions: the development of the RKCNN-MMBO model that showed a very high accuracy rate in attack detection. The limitations of the research are the large volume of data needed for the purpose of accurate model training and its high computational complexity. It highly emphasizes the efficiency of the RKCNN-MMBO model in improving the attack detection capability in IoT, accompanied by some suggestion for future work.

The article "HCRNNIDS: Hybrid Convolutional Recurrent Neural Network-Based Network Intrusion Detection System" [5] investigates and develops an intrusion detection system using a hybrid deep learning model consisting of Convolutional Neural Networks and Recurrent Neural Networks. The paper presents a proposed intrusion detection system that can predict and classify cyber-attacks Bloomfield and Nelson, the major contribution of this paper is the proposal of the HCRNNIDS model; it has an accuracy rate in attack detection as high as 97.75% with ten-fold cross-validation. The methodology used is based on the combination of convolutional neural network methods for the extraction of local features and recurrent neural network methods for the capture of temporal features in order to improve IDSs. The paper also discusses the limitations related to the extensive training data needed and the computational complexity in the accurate training of the model. The conclusion comments on the fact that the proposed HCRNNIDS model outperforms existing methods and can be taken as a new way of attack prediction in computer networks.

In [6] investigates the use of a BRNN for intrusion detection in IoT devices. In this paper, the considerable contributions made were related to the design of a BRNN model processing information from both temporal directions simultaneously: past and future, improving attack detection accuracy drastically. The methodology of the research also includes techniques for feature selection and parameter optimization using the Random Forest algorithm to increase model accuracy. Some limitations include that large datasets are needed for the proper training of the models, and in itself, BRNN has high computational complexity. The main contribution and conclusion are that the BRNN model outperforms conventional RNN and GRNN models and can be an effective security solution in IoT environments.

In [7] proposes an intelligent intrusion detection framework with deep learning algorithms for IoT networks. In the hybrid model, this paper uses RNN-GRU and can detect attacks on three layers: physical, network, and application. The steps performed in the research methodology include data preprocessing through cleaning, feature encoding, filtering, combining, and normalization. The self-imposed limitations in the study include that accurate training requires large datasets and high computational complexity. Considering such advantages, this method has to turn out much better than existing models.

The authors in [8] conducted research on using machine learning and deep learning to solve security problems in the internet of things (IoT) system. The research does the filtering of IoT threat video with the help of attack models for the initial attacks detection, to extract network traffic data for training the feature as well as for the database driven features for the detection of attacks. The accuracy is better, computational time is low with higher recall and G-mean. The paper also described category of algorithms including classification of CNNs and comparison between the accuracy and time run between them. It outlines the privacy and security in the IoT system and how ML and DL algorithm can guarantee those security and privacy.

In [9], a deep learning based GRU-RNN is developed for intrusion detection in SDN environment. Only 6 raw features from the NSL-KDD dataset is used to achieve accuracy of 89%. Experimental results confirm that the proposed approach does not impact network performance and therefore makes it a practical option for intrusion detection in SDN environments. The proposed GRU-RNN demonstrates that intrusion detection in SDN environments generated from the NSL-KDD dataset has an accuracy of 89%, which is better than other algorithms VanilaRNN, SVM and DNN in terms of Precision (P), Recall (R), F-measure (F) and Accuracy (AC). The suggested GRU-RNN reported a detections of 89% and 90% are raw footprints benign and anomalies, 0-day attacks exceed accuracy, Certainly, the GRU-RNNs method has directed better TPR and low FPR when compared with other algorithms, it also proved to have lesser false positive rate which is very congeal to a IDS. The proposed GRU-RNN model achieves an AC of anomaly detection of 89%, which is an enhancement over algorithms such as SVM, DNN, and NB Tree.

Table 1: Focus area, methodology, dataset, and major findings for the surveyed articles.

Table 1: Review of Articles

Title of the Paper	Key Findings	Dataset Used	Main Method	Focus Area
Intrusion Detection in IoT Using Deep Learning [3]	Deep learning models like CNN, GRU, and LSTM have shown high accuracy in detecting attacks.	N-BaIoT	CNN, GRU, LSTM	Attack detection in IoT
Intrusion Detection Model for IoT Using Recurrent Kernel Convolutional Neural Network [4]	The RKCNN-MMBO model has demonstrated very high accuracy in attack detection.	CICIDS-2017	RKCNN-MMBO	Cyber-attack detection
HCRNNIDS: Hybrid Convolutional Recurrent Neural Network-Based Network Intrusion Detection System [5]	Results indicate the superiority of the HCRNNIDS model with high accuracy in attack detection.	CSE-CIC-DS2018	CNN, RNN	Attack detection in IoT
Bi-directional Recurrent Neural Network for Intrusion Detection System (IDS) in the Internet of Things[6]	Using BRNN has significantly improved attack detection accuracy.	UNB ISCX 2012	BRNN	Attack detection in IoT
A Hybrid Deep Learning-Based Intrusion Detection System for IoT Networks [7]	The hybrid RNN-GRU model performs with high accuracy (up to 85%) in detecting attacks and outperforms other IDS models.	ToN-IoT	RNN-GRU	Attack detection in three-layer IoT architecture
Implementation of Machine Learning and Deep Learning for Securing the Devices in IOT Systems[8]	High accuracy, low false alarm rate, effective distinction between traffic types	NSL-KDD	LSTM-RNN algorithm	Identification system using LSTM-RNN
Deep Recurrent Neural Network for Intrusion Detection in SDN-based Networks [9]	High accuracy, low false alarm rate, effective distinction between traffic types	NSL-KDD	LSTM-RNN architecture	Identification system using LSTM-RNN

3- Background and Explanation

Cybersecurity within the Internet of Things grew and is still growing to become the most critical issue in the domain of Information Technology, as the number and diversity of devices connected with the advent of their various wide-range applications grow drastically. In general, IoT allows devices and systems to communicate with each other and share data over the internet [10]. While stimulating a wide array of processes, it also opens up new security threats that need special attention. Notably, detection and countering cyber-attacks are some of the challenges that naturally come along with these kinds of networks and have turned into an obstacle [11].

The researchers have been working substantially in the security of the IoT devices for the past years. Since the concept concerned researchers, ways to protect those devices from attacks have been found. The first efforts that were put in were initially traditional security methods, like firewalls, Intrusion Detection Systems, among others. All these methods proved insufficient due to the enormous volume and complexity of data involved. Due to advancement in technologies and innovations in machine learning and deep learning algorithms, more advanced approaches for attack detection have been developed that can analyze and process large volumes of data more accurately.

Deep learning algorithms have evolved to become an industry standard in the process of intrusion detection in any IoT network today [12]. Challenges like class imbalance and the requirement for exact feature optimization, however, still exist to a great extent. In this paper, these have been addressed through the use of PSO.

Particle Swarm Optimization algorithm is a population-based optimization method, inspired by the collective behavior of birds and fish [13]. It considers a swarm of particles moving through the search space to search for the optimal solution. Each particle thus updates the position based on its experience and experience of other particles, which converges finally to get the best solution [١٤]. In this work, PSO is applied for selecting key features from IoT data in order to enhance the accuracy and efficiency of deep learning models.

Below is the pseudocode and flowchart of the particle swarm optimization algorithm.

Pseudocode for Particle Swarm Optimization (PSO)
1. Initialize parameters: - Define the number of particles. - Define inertia weight, cognitive constant, and social constant. - Initialize the position of each particle randomly. - Initialize the velocity of each particle randomly. - Initialize the best known position (pBest) for each particle to its initial position. - Initialize the global best position (gBest) to the best initial position among all particles. 2. Evaluate: - Calculate the fitness value for each particle based on the objective function. - If a particle's current position is better than its pBest, update pBest to the current position. - If a particle's current position is better than the gBest, update gBest to the current position. 3. Update velocity and position: - For each particle, update its velocity using the formula: velocity = inertia * velocity + cognitive * random() * (pBest - position) + social * random() * (gBest - position) - Update the position of each particle using the formula: position = position + velocity 4. Check termination criteria: - If the stopping criterion (e.g., maximum number of iterations or desired accuracy) is met, stop the algorithm. - Otherwise, go back to step 2. 5. Output: - The global best position (gBest) is the solution to the optimization problem.

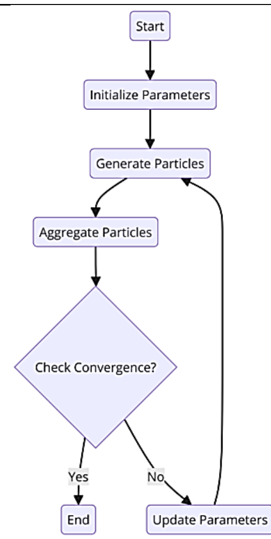

Fig. 1 Particle Aggregation Algorithm Flowchart [13]

4- Model and System Framework

The main aim of this paper is to enhance the capability of fast and accurate detection of attacks on IoT networks to prevent any system problem. In this regard, we consider the application of the following deep learning algorithms: Convolutional Neural Network, Gated Recurrent Unit, and Long Short-Term Memory. Besides, in the process of hyperparameter optimization, the work applies the algorithm of particle swarm optimization. The details of the proposed approach are summarized below and further elaborated with the help of a pseudocode representation

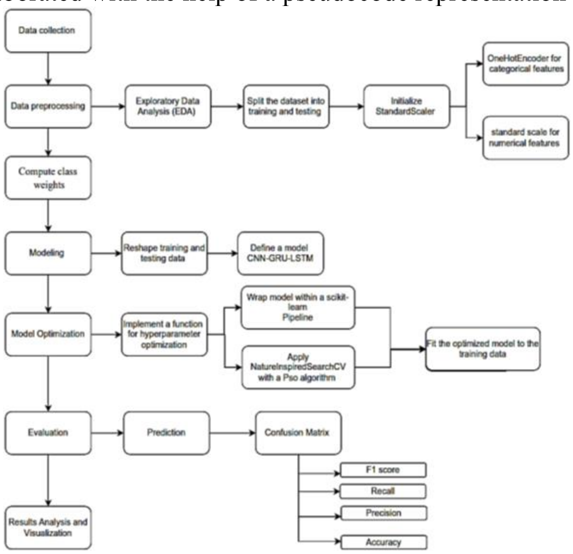

Fig. 1 Flowchart of the proposed method (researcher)

Pseudo Code
1. Data Collection - Collect data from the source. 2. Data Preprocessing - Perform Exploratory Data Analysis (EDA). - Split the dataset into training and testing sets. - Initialize StandardScaler for numerical features. - Apply OneHotEncoder for categorical features. 3. Compute Class Weights - Calculate class weights for handling class imbalance. 4. Modeling - Reshape training and testing data as needed. - Define the CNN-GRU-LSTM model architecture. - Wrap the model within a scikit-learn Pipeline. 5. Model Optimization - Implement a function for hyperparameter optimization. - Apply NatureInspiredSearchCV with a Particle Swarm Optimization (PSO) algorithm. - Fit the optimized model to the training data. 6. Evaluation - Make predictions using the optimized model. - Compute and display the Confusion Matrix. 7. Results Analysis and Visualization - Calculate evaluation metrics: F1 score, Recall, Precision, and Accuracy. - Visualize the results using appropriate plots.

In this look at, we gift a complete gadget version and framework for developing and comparing a hybrid CNN-GRU-LSTM model aimed at improving intrusion detection skills in Internet of Things (IoT) networks. This technique leverages Convolutional Neural Networks (CNN), Gated Recurrent Units (GRU), and Long Short-Term Memory (LSTM) networks to address the complexity and evolving nature of safety threats in networked environments.

The initial segment of our methodology entails statistics series and preprocessing the use of the UNSW_NB15 dataset, a widespread dataset hired in network intrusion detection research. The records undergo preprocessing steps which include disposing of identifier columns and encoding the goal column the use of LabelEncoder to convert specific labels into numerical format appropriate for version processing. Missing values are handled to ensure that no facts gaps affect the schooling system. Additionally, numerical functions are normalized the usage of StandardScaler, and express functions are converted using OneHotEncoder to put together the records for powerful model input.

Exploratory Data Analysis (EDA) is conducted to study elegance distribution and pick out any imbalances that might bias the version's education and prediction accuracy. To mitigate the effect of class imbalance on model overall performance, elegance weights are calculated primarily based at the inverse frequency of class occurrences within the schooling statistics. This method guarantees a balanced education surroundings, allowing the version to analyze equitably across all class labels.

The model structure is designed to leverage the strengths of both convolutional and recurrent neural network technologies. The version starts off evolved with an preliminary convolutional layer that applies convolution operations to capture spatial hierarchies and functions from the input records, followed by using a max pooling layer that reduces records dimensionality, thereby decreasing model complexity without dropping vital facts. Subsequent layers consist of GRU and LSTM units, which excel at taking pictures temporal dependencies and long-time period relationships in the information, critical for detecting complex intrusion sports over the years. The community concludes with a Dense layer that transforms the processed features into the final output used for class.

We tune or optimize our model using a nature-inspired algorithm, particularly the Particle Swarm Optimization algorithm. This algorithm will help in hyperparameter tuning by guided search in the parameter space through the social behavior of a flock of birds for finding an optimum solution in a natural way. Hence, this step-in optimization is important to adapt the unique characteristics of the dataset, as the model would learn such characteristics and performances in this dataset, hence augmenting its accuracy and generalization capability.

Model performance assessment is performed in terms of several metrics, such as mean squared error, mean absolute error, R-squared values, and the correlation coefficient between the predicted and actual values. All these metrics give an in-depth understanding of predictive models in terms of their accuracy and efficiency. Evaluation confirms the model's ability to generalize to new, unseen data and also shows that it can be very useful in a real-world scenario where one needs a reliable and robust intrusion detection system.

In this respect, the present study has developed a very potent framework of intrusion detection in Internet of Things networks by implementing newer concepts of machine learning and optimization algorithms. The combination of an integrated model of CNN, GRU, and LSTM further optimized with PSO makes the scheme very effective in managing major challenges in the respective field and opens further avenues for enhancing network security technologies. That is to say, the embedding of these two deep learning architectures could be a giant leap in the development of adaptable, efficient, and accurate security systems against a sequence of attacks within any setup of a complex network.

Data Used for Simulations

Through this research, UNSW-NB15 dataset. This data set of raw network packets was generated by the IXIA PerfectStorm device in UNSW Canberra Cyber Range Lab. This dataset was used to provide a complete set of new normal activities and synthetic attack behaviors. The features considered in this data are vast in number, including those directly extracted from network traffic, such as IP addresses, ports, protocols, temporal ones, and transferred volumetric data.

5- Findings and Results Analysis

In this paper, we designed and carried out a singular hybrid deep mastering algorithm for proactive assault detection in Internet of Things (IoT) networks. This hybrid set of rules makes use of CNN, GRU, and LSTM architectures and enhances its performance the use of Particle Swarm Optimization (PSO) for hyperparameter choice. To evaluate the efficiency of this hybrid model, we compared it with RNN, LSTM-RNN, GRU, and GRU-CNN algorithms. This assessment is primarily based on 4 number one evaluation metrics: accuracy, precision, bear in mind, and F1 score. These metrics enable us to evaluate the model's ability to accurately detect assaults in real-world environments with imbalanced records.

1. Accuracy:
- It is the metric that estimates how accurate is the algorithm in detecting attacks and non-attacks [15].

$$\text{Accuracy} = \frac{\text{True Positive} + \text{True Negative}}{\text{True Positive} + \text{True Negative} + \text{False Positive} + \text{False Negative}} \quad (1)$$

2. Precision:
- This metric measures the proficiency of the algorithm in raising an alarm when an attack has really taken place [16].

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} \quad (2)$$

3. Recall:
- This metric measures the set of rules's fulfillment in identifying real assaults as compared to the total real assaults [17].

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \quad (3)$$

4. F1 Score:
- This metric combines precision and recall to symbolize the balance between these two measures [17].

$$\text{F1 Score} = \frac{2\times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (4)$$

In this phase, we gift the parameters and hyperparameters used to optimize the PSO set of rules. The intention of this optimization is to successfully track the parameters of the hybrid CNN-GRU-LSTM version to reap the highest accuracy in detecting attacks in IoT networks.

Table 2: Hyperparameters Used in the Model

Functional Parameter	Values
Activation Function	RELU, SELU
Neurons per Layer	75, 150
Regularization	L1, L2
Learning Rate	0.001, 0.004

These are carefully chosen hyperparameters so that the model is estimated to be able to capture all complex patterns that might be intrinsic in IoT network traffic data. Moreover, we considered additional activation functions, regularization settings, number of neurons per layer, and learning rates for examining their role in the overall performance of the model and choosing the best one to provide the highest detection accuracy.

This paper shows that many critical hyper-parameters can be optimized for optimal performance of a Hybrid CNN-GRU-LSTM model designed for attack detection in IoT networks. These were opted such that the possibilities of overfitting reduce with optimum performance of the model.

Activation Function: We considered not unusual activation features, RELU and SELU, to be used in distinctive layers of the neural community. These capabilities were selected for their capability to help accelerate community convergence and reduce the vanishing gradient problem.

Regularizes: To cope with overfitting, two sorts of regularizes, L1 and L2, have been employed. These regularizes help the version by means of diminishing insignificant weights and preserving most effective meaningful functions.

Neurons in keeping with Layer: Based on trial and error, neuron counts have been decided on: 75 and 150. This configuration permits for modeling the complexities of IoT information by means of presenting sufficient flexibility to the community.

Learning Rate: Two mastering fees, zero.001 and 0.004, were used to alter the velocity of weight updates throughout the education process. Different learning charges permit us to find the right balance among gaining knowledge of velocity and version accuracy.

Below, Table 3 presents the parameters used by the PSO set of rules.

Table 3: PSO Algorithm Parameters

Parameter	Description	Selected Values
w	Inertia coefficient controlling the influence of previous motion of particles	0.7
c1	Personal coefficient that determines the attraction of particles to their best, previously found position.	1.5
c2	Social coefficient relating particle attraction strength to the group's global best position	1.5
v_min	Minimum particle velocity, which constrains the possible movement of particles in the search space of a problem	-1
v_max	The maximum velocity of particles, thus limiting the maximum perturbation of a particle within the search space.	1

These parameters have been tuned in a way that balances the exploration and exploitation of the search space so that PSO algorithm would find the global optimal set of parameters for which the model would elude local minima and improve in convergence rate for proactive attack detection in IoT networks.

Results after running the PSO algorithm were the best values selected, stored, and used in training the final model. Parameters optimized by PSO are shown below.

Table 3: PSO algorithm parameters

Parameter	Selected Value
Activation Function	RELU
Neurons per Layer	150
Regularization	L2
Learning Rate	0.001
w (Inertia)	0.7
c1 (Personal Coeff.)	1.5
c2 (Social Coeff.)	1.5
v_min (Min Velocity)	-1
v_max (Max Velocity)	1

Table 4: Best Values Selected Using the PSO Algorithm

L1	Regularizes	RELU	Activation Function
0.001	Learning Rate	150	Neurons per Layer

We now gift the results from the training and checking out levels of the model, illustrated via performance statistics. This information demonstrates how the hybrid CNN-GRU-LSTM model, utilizing superior optimization algorithms and deep learning, has completed excessive accuracy in detecting assaults in IoT networks. The outcomes from each the training and trying out facts are special within the desk below, highlighting the version's success in each phase.

Table 5: Model Performance Results on Training and Testing Data

Metric	Training Data	Testing Data
Accuracy	93.8%	93.24%
Precision	90.3%	89.00%
Recall	92.2%	91.00%
F1 Score	91.5%	90.00%
ROC AUC	94.15%	93.24%

These numbers spell out high model capability in the correct detection of attacks across IoT networks, the result of model architecture and learning process optimizations. The training data points to the high adaptability of the model to the dataset used in training; the test data, on the other hand, offers practical proof of how this model will perform in real life.

In the next segment, we evaluate the proposed hybrid model, which incorporates CNN, GRU, and LSTM architectures, with other algorithms typically utilized in deep studying for attack detection. These algorithms consist of RNN, LSTM-RNN, GRU, and GRU-CNN. The goal of this contrast is to evaluate the relative overall performance of the hybrid model in opposition to different conventional procedures and decide the volume of development this hybrid combination can provide in phrases of detection accuracy and performance.

The contrast effects are displayed in the desk beneath, which incorporates key metrics along with accuracy, precision, consider, and F1 rating for each algorithm. This fact helps us gain a higher know-how of each model's abilities while dealing with complex and imbalanced facts.

Table 6: Simulation Results

Algorithm	Accuracy	Precision	Recall	F1 Score
Proposed Model	93.24%	89.00%	91.00%	90.00%
RNN	89.50%	85.00%	88.00%	86.50%
LSTM-RNN	91.00%	87.00%	89.50%	88.25%
GRU	92.00%	88.50%	90.00%	89.25%
GRU-CNN	92.50%	88.75%	90.50%	89.62%

The analysis of the information in the assessment results desk suggests that the proposed hybrid version (CNN-GRU-LSTM) has efficiently outperformed different fashions below evaluation, consisting of RNN, LSTM-RNN, GRU, and GRU-CNN. This improvement in overall performance, in particular in precision and F1 score metrics, indicates that combining one of a kind deep getting to know architectures with unique parameter and characteristic optimization thru the PSO algorithm extensively enhances the version's potential to correctly and efficiently stumble on assaults in imbalanced and complicated environments. This analysis demonstrates that superior and hybrid strategies in constructing deep studying models can be tremendously powerful in addressing challenges in figuring out complicated records styles.

The following figure shows the confusion matrices for all of the models that are being compared to in this paper. The reason for such charts is to get a broader assessment and analysis of the performance of the models in correctly and, wrongly, diagnosing the data classes.

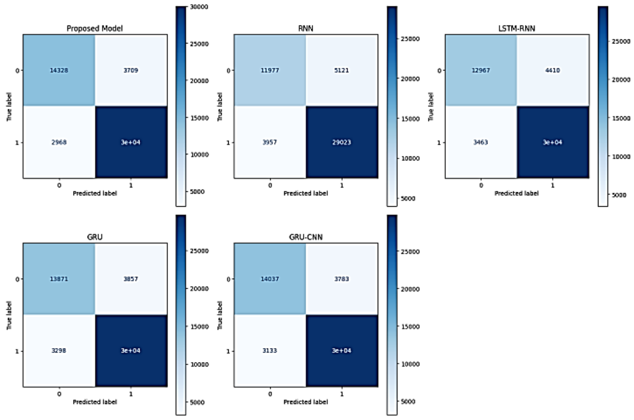

Fig. 1 confusion matrix

Using the confusion matrices, a complete understanding of the accuracy of the classification for all models, including the CNN-GRU-LSTM hybrid proposed in this work and five others, RNN, LSTM-RNN, GRU, and GRU-CNN is given. The performance metrics do suggest that the proposed model rightly identifies more number of samples correctly as indicated by the true positives and true negatives and is lower in error rates to the other models. This shows that the model performs well to identify between various classes of data with the least possible discrepancies as compared to RNN and LSTM-RNN which have provided nearly wrong readings for both the positive and negative samples. Furthermore, it is evident that the combined CNN-GRU-LSTM has the strength of each of the architectures and saves much less erroneous calculations and improves its generality. Comparatively, there are drawbacks related to simpler models which run into what are referred to as complex patterns of data and results in higher error rates. Indeed, this analysis emphasizes that it is possible to increase classification model accuracy and reliability by utilizing excellent hybrid combinations of the architectures described above, particularly when working with skewed or multimodal datasets.
Additionally, evaluating the hybrid model's overall performance with different fashions reveals that integrating layers with complementary talents, inclusive of GRU and LSTM layers mixed with CNN layers, complements the model's detection and discrimination capabilities. This integration improves the precise detection of touchy and essential statistics areas, in the end main to better standard model accuracy in actual-world situations. Therefore, evaluation strategies primarily based on a couple of metrics, which includes ROC AUC, are specifically vital in reading model performance in diverse check and schooling eventualities. These analyses provide a scientific foundation for better expertise and continuously optimizing deep studying fashions to evolve to actual facts and lay the basis for future improvements in detection and safety technology.
In this section of the research, we expose the limitations encountered in this study. Knowing the limitations would provide a more accurate rendering of the results and help future studies in enhancing these models.

5-1- Data Limitations:

- The facts used in this observe might not comprehensively cover all aspects of protection threats in IoT networks. Specifically, the restricted availability of datasets containing real and up to date assault statistics can have an effect on the algorithms' capability to train and test correctly. This obstacle is specifically full-size while the model needs to pick out new and rising assaults.

5-2- Computational Limitations:

- Implementing the hybrid algorithms and optimizations used in this research, mainly genetic and PSO algorithms, calls for excessive computational electricity and hardware resources. This can be difficult in environments with restrained resources. High computational complexity may also growth operational expenses and create boundaries for the extensive deployment and sensible software of these models in the industry.

These limitations impact the development and development of the proposed models and have to be addressed in destiny research thru progressive strategies and new technologies. Understanding these obstacles allows choice- makers and researchers expand more effective strategies for applying the effects of this take a look at in actual-international situations.

6- Conclusion

In this paper, we focused on the design and implementation of a hybrid CNN-GRU-LSTM model targeted at enhancing the security in IoT networks. The model integrates big data analytics with deep learning and PSO for a more robust and proactive mechanism against cyber threats. Much emphasis is given to the precise selection of hyperparameters through the PSO optimization process to increase the model's accuracy in attack detection.
Evaluations showed that at the very least, the proposed algorithm outperformed other state-of-the-art models like RNN, LSTM-RNN, GRU, and GRU-CNN. Specifically, created results of this comparison in metrics such as ROC-AUC, F1 Score, Recall, Precision, and Accuracy proved the effect of this hybrid approach. This model has advantages not only in theoretical power but also in practical applicability, and thus can hugely enhance IoT security in real-world scenarios.

This paper has illustrated that recent deep learning algorithms along with optimization algorithms could be one of the excellent solutions for solving the security issues of IoT. Considering these results, the organizations dealing with IoT Technologies can use this model in their defensive strategies and make the data and connected devices associated secure.

Future Research Recommendations:

- Hyperparameter Optimization: The hyperparameter optimization may be performed a whole lot deeper, and greater superior techniques of PSO may be used for similarly overall performance improvement.
- Scalability: Whether this algorithm scales to more complicated and larger IoT environments and at what level, in order that proposed answers are nonetheless powerful in larger dimensions.
- Field Deployment: Partner with industrial partners for the checking out of the fashions with the aid of actual-international deployments that generate critical feedback about the effectiveness and performance of the answers in real conditions.

This research is a sizable step in growing deep learning-primarily based protection answers for IoT networks and sets the level for destiny advancements in this area.

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Journal of Information Systems and Telecommunication
Vol.13, No.2, April-June 2025, 139-153

http://jist.acecr.org
ISSN 2322-1437 / EISSN:2345-2773

NeuroIS: a State-of- the- Art Analysis

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Received: 07 Jul 2024/ Revised: 04 Apr 2025/ Accepted: 07 May 2025

Abstract

NeuroIS, the interdisciplinary field merging neuroscience and information systems, has recently garnered significant attention for its potential to enhance our understanding of human behavior in the tech context. This analysis delves into the current NeuroIS research landscape, examining key trends, methodologies, and discoveries in the field. By synthesizing recent research, the aim is to shed light on potential applications of NeuroIS across various domains and identify future research directions in this rapidly evolving field. Currently an emerging area within information systems, NeuroIS has a limited number of studies available. To aid researchers entering NeuroIS, we have analyzed 244 articles and summarize their findings to give more details of NeuroIS studies. This examination of literature reveals various avenues for future NeuroIS exploration, including influencing factors, measurement tools, and subject areas. We believe that our work will offer valuable insights for upcoming NeuroIS studies. The fusion of neuroscience and information systems holds immense potential for uncovering profound insights into human-computer interaction, decision-making processes, cognitive responses to technology, and enhancement of user experiences. As the field progresses, researchers are increasingly exploring innovative methods such as functional magnetic resonance imaging (fMRI), electroencephalography (EEG), and eye-tracking to unravel the complex mechanisms underlying human cognition in the digital age. By delving into the neurobiological basis of technology-mediated interactions, NeuroIS presents opportunities for designing more intuitive, efficient, and user-centric systems. With numerous uncharted research paths ahead, the future of NeuroIS looks promising, signaling a potential shift in how we understand and utilize information systems to impact human behaviors and decisions.

Keywords: NeuroIS; Information Systems (IS); Human-Computer Interaction (HCI); Neuroscience; State-of-the-art.

1- Introduction

The utilization of cognitive neuroscience in information management represents a novel research approach within the realm of information systems, which has emerged in recent years under the banner of neural information systems, or NeuroIS. NeuroIS, a subfield of information systems (IS), harnesses neuroscience and neurophysiological tools and knowledge to gain deeper insights into information systems phenomena [1]. It serves as a crucial bridge between neuroscience, psychology, and information systems research, facilitating the examination of the impact of new technology and its utilization. The research findings derived from this approach can provide valuable guidance for the development of new information system designs and applications [2].

NeuroIS endeavors to comprehend the internal processes that underlie human behavior within the context of information systems by leveraging theories and tools from neuroscience and related disciplines. Its overarching goal is to make significant contributions, such as informing the design of IT artifacts, introducing a biological level of analysis as a mediator between IT artifact and IT behavior, elucidating the theoretical mechanisms that underlie the influence of IT artifacts on IT behavior, and offering additional avenues for the evaluation of IT artifacts [3]. Although the field is still considered nascent within the domain of information systems, further endeavors are imperative to advance it from both theoretical and methodological standpoints.

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This paper provides a comprehensive overview of the genesis and current status of NeuroIS, commencing with the definition of NeuroIS and delving into its developmental trajectory. Section 2 outlines the current state of development of NeuroIS and literature background. While Section 3 expounds upon the Research Methodology. Section 4 presents Number of the NeuroIS related publications. Section 5 expounds Contributions of neuroscience to IS research. Section 6 categorizes neuroscience theories in NeuroIS. Section 7 introduces the thematic orientation of NeuroIS research. Section 8 presents Analysis of Methodological of NeuroIS Researches. Section 9 outlines Analysis of Areas of NeuroIS Research. Section 10 delves into Disruptive technologies and Tools in NeuroIS research. Section 11 outlines the conclusion, summarizes the development of this paper and NeuroIS.

2- Literature Background

2-1- The Origins and Development of NeuroIS

NeuroIS (Neuro-Information-Systems), is an interdisciplinary field within information systems that utilizes neuroscience and neurophysiological tools and theories to gain a deeper understanding of the development, adoption, and impact of information and communication technologies.

The concept of applying cognitive neuroscience approaches in IS research was first introduced at the 2007 International Conference on Information Systems (ICIS), and the term "NeuroIS" was coined by Dimoka et al. (2007).

NeuroIS aims to achieve two main goals. Firstly, it seeks to contribute to an advanced theoretical understanding of the design, development, use, and impact of information and communication technologies. Secondly, it aims to contribute to the design and development of IT systems that have a positive effect on practical outcome variables such as health, well-being, satisfaction, adoption, and productivity.

Since 2009, an annual academic conference has been organized to present research and development projects at the intersection of IS and neurobiology. The goal of this event is to facilitate the successful development of the NeuroIS field.

Topics explored in NeuroIS research include conceptual and empirical works, as well as theoretical and design science research. It encompasses a wide range of neuroscience and neurophysiological tools, including techniques such as functional magnetic resonance imaging

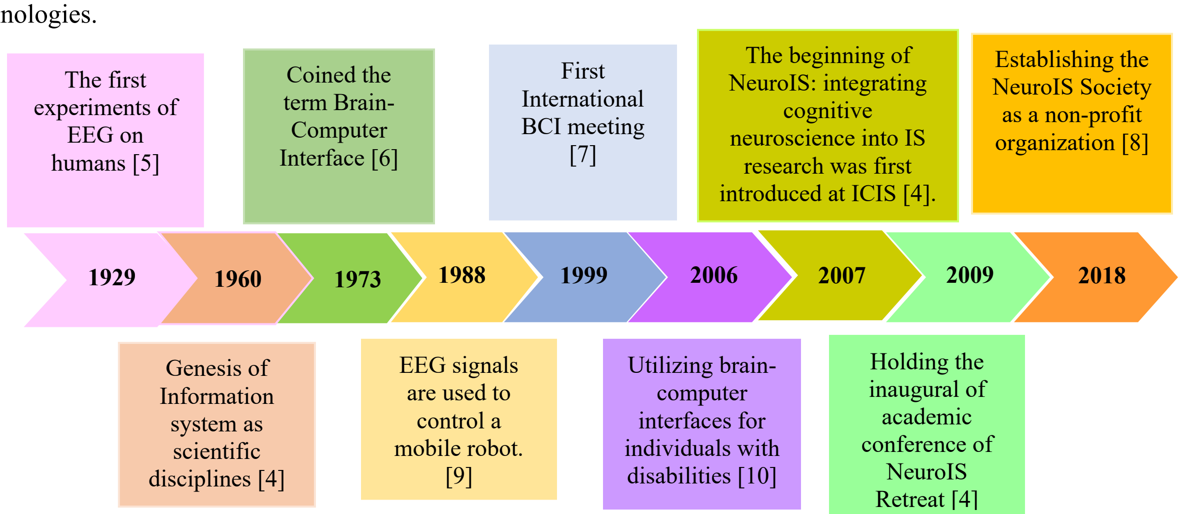

Figure 1.Timeline of the genesis and development of NeuroIS (Source: authors)

(FMRI), electroencephalography (EEG), hormone assessments, skin conductance and heart rate measurement, eye-tracking, and facial electromyography. Additionally, it is anticipated that quantitative and molecular genetics will play a role in future NeuroIS research [4]. Over the years, NeuroIS has gained momentum and recognition, with an increasing number of studies and applications emerging across different domains.

ffering new insights and opportunities for understanding human behavior and cognition in the context of information systems. Figure1 shows the timeline of the emergence and development of NeuroIS.

2-2- The Integration of Neuroscience and Information Systems

IS research aims to describe, explain, predict, and design IT phenomena, drawing on knowledge and methods from diverse reference disciplines. This interdisciplinary influence allows IS research to address four levels of analysis: individual, group, organization, and society [11]. Various research methods, including laboratory experiments, surveys, case studies, action research, design science methods, and mathematical methods, have been employed in IS research. There is a need for the IS field to update and strengthen its investigative approaches to continue progressing. For example, knowledge of the neurobiology of learning, memory, and attention can inform the design of user interfaces. As many constructs in IS research are associated with human information and decision behavior, insights from neuropsychology and cognitive neuroscience can inform the study of a wide range of IS phenomena.

research, and NeuroIS itself will contribute knowledge to these reference disciplines.

Several research fields and disciplines are important references for NeuroIS research. These fields include biology and medicine, as well as engineering and computer science. Insights from biology and medicine tend to contribute more to theoretical research than design research. Additionally, insights from engineering and computer science tend to contribute more to design research than theoretical research [1]. From an IS perspective, disciplines such as neuropsychology, cognitive neuroscience, neuroeconomics, decision and social neuroscience are considered fundamental research, while neuromarketing and consumer neuroscience, neuroergonomics, affective computing, and brain-computer interaction are more often associated with applied research. As technology continues

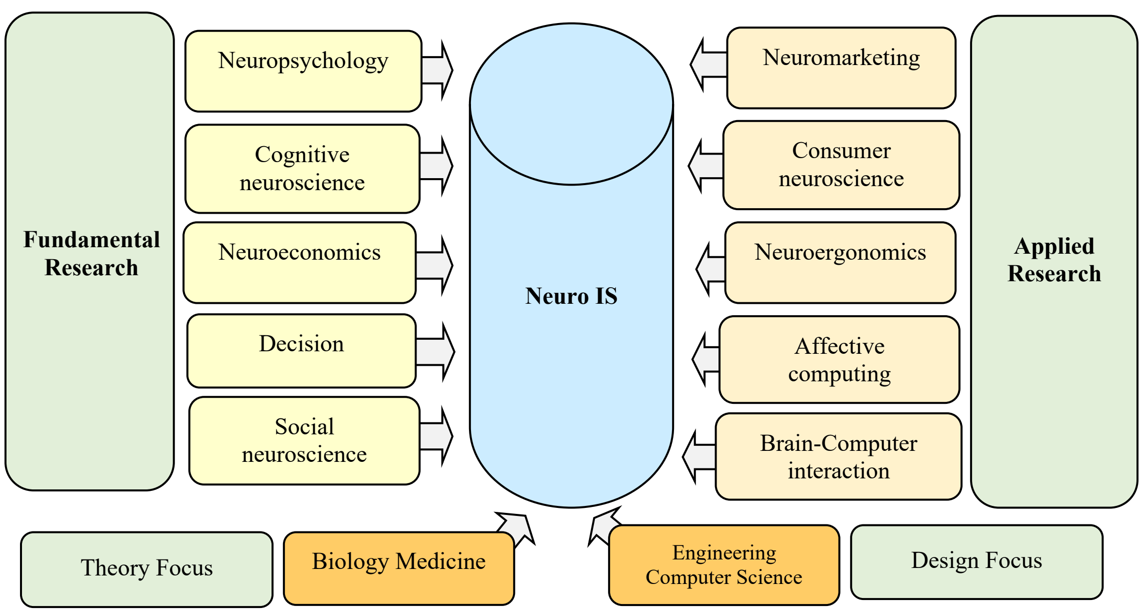

Figure 2. Reference disciplines of NeuroIS (Adapted from: [11])

to advance, the potential applications of NeuroIS are expected to expand, making it an exciting and dynamic field of study. Figure 2 distinguishes between theory-focused and design-focused research, as well as fundamental and applied research [11].

As the NeuroIS field matures, it is expected that new reference disciplines will emerge, some of the existing reference disciplines will become more important for IS

2-3- Applications of NeuroIS

Some potential applications of NeuroIS include improving user interfaces for software systems, enhancing the design of online advertisements to better capture attention and engagement, and optimizing the layout and content of websites to maximize user satisfaction and task performance. Additionally, NeuroIS can be used to develop more effective training programs and decision support systems by understanding how users process information and make decisions (Table 1).

Table 1. Applications neuroscience in information systems

Applications	***Attributes***
User Experience Research and designing user interfaces	Using neuroimaging techniques such as fMRI (functional Magnetic Resonance Imaging) and EEG (Electroencephalography) to study users' cognitive and emotional responses to different interfaces and design elements. This can help in designing more user-friendly and effective systems [12].
E-Commerce and designing of online advertisements	Neuromarketing: Applying neuroimaging and psychophysiological techniques to understand consumers' responses to marketing stimuli such as advertisements, product designs, and branding. This can provide insights into consumer preferences and decision-making processes [13].
Information Security	Studying the neural correlates of security threats and decision-making to develop more effective security measures and policies. This can help in designing systems that are more resistant to human error and manipulation [14][15].
Healthcare Systems	Using neuroimaging and physiological monitoring to improve the design of healthcare systems, such as electronic health records and medical devices, to enhance patient safety and user experience [16].
Education and Training	Applying neuroscientific principles to develop more effective e-learning systems and training programs. This can help in optimizing the delivery of educational content and improving learning outcomes [17].
Financial Decision Making	Studying the neural mechanisms underlying financial decision-making to develop better decision support systems and tools for investors and financial professionals [18].

3- Research Methodology

This paper presents a thorough and unified analysis of the current status of NeuroIS. Our approach is rooted in the latest advancements in the field, aiming to uncover ongoing scholarly discussions, examine key findings, and outline future directions. In contrast to conventional literature reviews, the Systematic Review of Literature (SRL) offers numerous advantages, such as mitigating bias and ensuring transparency and reproducibility [19].

The main objective of this study is to provide a comprehensive and coherent overview of NeuroIS, to provide insight into its practical application, and to evaluate factors influencing its adoption in IS research. According to the research process (Figure 3), a search was first conducted in the Elsevier Scopus database to identify relevant studies. Inclusion criteria included articles written in English, and the review period between 2000 and 2024 included articles, conference papers, book chapters, and reviews. The keyword "NeuroIS" was searched, and the title, keyword, and abstract fields. Then articles full text were examined and 244 articles were extracted from the Scopus database and discussed and analyzed.

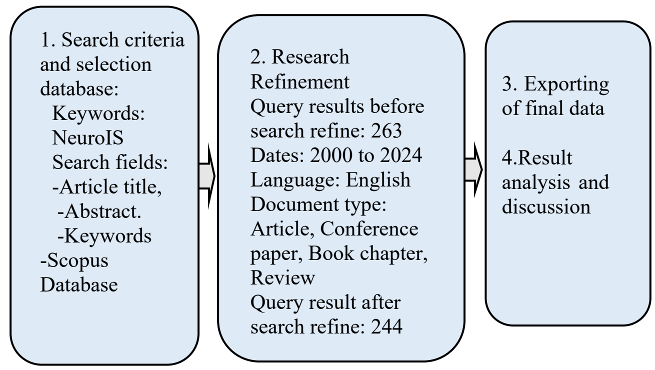

Figure 3. Framework research methodology (Source: [19]).

4- Number of the NeuroIS Related Publications

Scopus is a web-based multidisciplinary literature database. It is the world's largest comprehensive academic information resource covering various disciplines. It includes core academic journals influential in fields like natural sciences, engineering technology, and biomedicine. Thus, we analyze the development of NeuroIS by counting the NeuroIS-related publications in this database. As of February 17, 2024, 263 NeuroIS-related publications have been found. Figure 4 shows the publication numbers over the years, revealing four stages of NeuroIS development: Embryonic Stage, Primary Stage, Ebb Stage, and Development Stage.

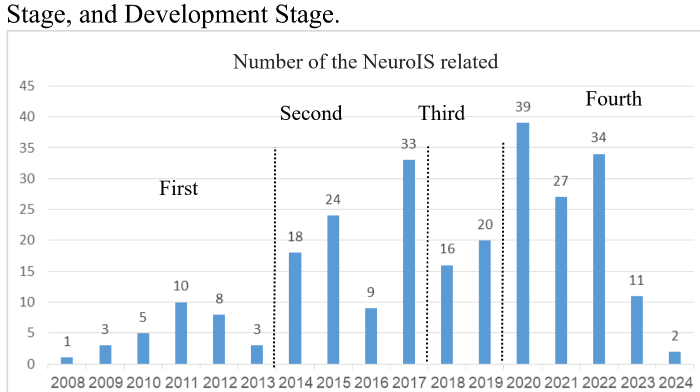

Figure 4. Publications in Scopus statistics chart

The embryonic stage includes the emergence of NeuroIS in 2007 and the annual holding of NeuroIS conferences since

2009. In the initial stage, we see the growth of publications in the field of NeuroIS. In the decline stage, the number of publications in the field of NeuroIS has decreased, but in the growth stage and using disruptive technologies in this field, we again see the growth of publications and innovation in published studies and research in the field of NeuroIS.

5- Contributions of Neuroscience to IS Research

NeuroIS has various applications across different domains and focuses on various research areas such as technology adoption, mental workload, website design, virtual worlds, and emotions in human-computer interaction, IT security, and other related topics. The ways in which neuroscience contributes to IS research are summarized in Figure 5. [4]. See Table 2. (In this section, the review articles that discussed and expressed the general definition of neurois were removed and only 221 articles were reviewed.)
The review of studies shows (Figure 6**)** that the greatest number of articles (34 articles) were published in relation to contribution 9, which focuses on "Using real-time information about the user's biological state in information systems research and design of biofeedback systems," while the fewest articles (15 articles) were published in relation to contribution 4, which pertains to "Brain activity and other biological responses can inform the evaluation of IT tools.
“It’s evident that contribution 9 has garnered significant attention within the academic community, likely due to the growing interest in leveraging real-time biological data for the advancement of information systems and biofeedback technology. On the other hand, contribution 4, despite its relevance in evaluating IT tools using biological responses, seems to have received comparatively less focus. This discrepancy in article publication numbers underscores the varying degrees of emphasis placed on different aspects of biological state utilization within the realm of information systems research and design.

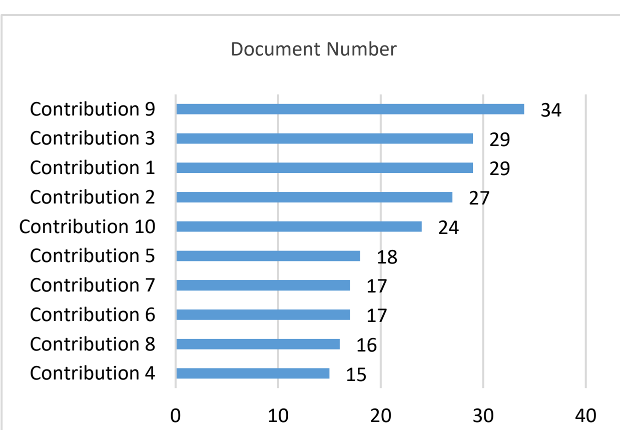

Figure 6. Articles published based on neuroscience contributions to IS research (N=221)

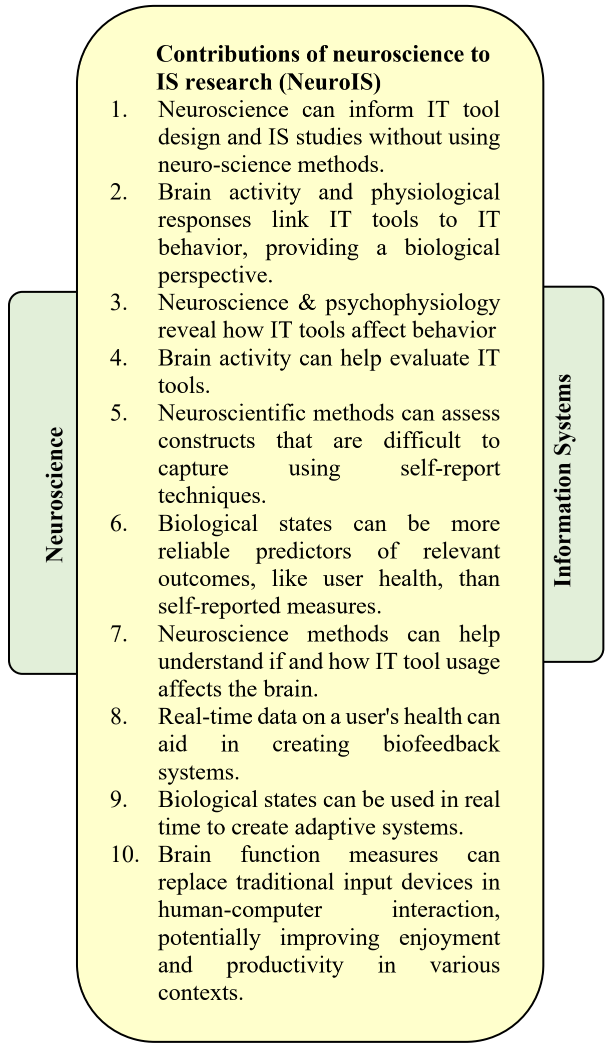

Figure 5. Contributions of neuroscience to IS research
(Adapted from: [11])

Table 2. Contributions of neuroscience to IS research

Contributions	*Attributes*	*Major themes/ application*	*Studies (N)*

Contribution 1	Neuroscience theories and literature play a crucial role in informing design decisions and can contribute in various specific ways. They can enhance the motivation for future behavioral IS studies, aid in the design of behavioral experiments and other forms of empirical inquiry, provide support for behavioral conclusions, and challenge existing assumptions and theories.	design decisions/ design and development of an IT artifact- design of behavioral experiments- theory development/test and design-oriented works	29
Contribution 2	The use of neuroscience and psychophysiological methods provides a deeper understanding of the impact of IT artifacts and introduces a new level of analysis in IS research by considering individuals' biological systems alongside the traditional levels of analysis.	brain activity patterns- biological systems / actual purchase decisions	27
Contribution 3	By studying brain activity and physiological responses, researchers can gain insights into the cognitive processes involved in using IT tools and how they impact decision-making, attention, and problem-solving. These methods can provide a more nuanced understanding of the ways in which IT tools shape behavior and inform the development of more effective and user-friendly technologies.	IT behavior/ the trustworthiness of the online shop- increased number of purchases	29
Contribution 4	Monitoring brain activity and using new software can give insight into user experience and cognitive load. Tracking physiological responses like heart rate and skin conductance can assess the impact of IT tools on stress and well-being. Incorporating these measures can help organizations understand how IT tools affect users and make informed decisions.	design of IT artifacts/ trust-IT artifact evaluation	15
Contribution 5	Neuroscience methods offer a more precise way to assess automaticity in IT use, leading to a deeper understanding of cognitive processes and behaviors. By measuring neural activity and physiological responses, we can uncover unconscious patterns of IT use, providing comprehensive insights into the impact of technology on the brain and behavior.	Automaticity/ affect reliability of data	18
Contribution 6	Biological measures can be objectively quantified and monitored over time, providing a more reliable and consistent source of data for predicting relevant outcomes.	Prediction/ hormone assessments- technostress	17
Contribution 7	Studying brain activity during IT tasks reveals insights into cognitive processes and neural mechanisms in technology use. Neuroscientific methods offer valuable data on IT' is long-term impact on brain structure and function.	alters the brain/ addiction- multitasking performance	17
Contribution 8	By leveraging real-time physiological and biochemical information, we can develop personalized interventions and solutions that cater to individual needs, ultimately leading to improved overall performance and quality of life.	neuroadaptive system / design adaptive systems- Design science research	16
Contribution 9	Biofeedback systems offer insights into a person's physical responses, allowing for personalized interventions to reduce stress and improve well-being. Using real-time data, they provide tailored strategies for managing stress, enhancing mental clarity, and optimizing performance in life.	Biofeedback systems/consciously control the physiological indicator	34
Contribution 10	This tech can change how we use computers, making it more intuitive and natural. It can eliminate the need for physical input devices, allowing for faster interaction and enhancing how work and play.	Brain-computer interfacing (BCI) human-computer interaction (HCI)/ video games- enterprise systems- commercial contexts- business domain	24

6- Classification of Neuroscience Theories in NeuroIS

The definition of theory in neuroscience is complex and varies among scholars. Gregor et al. (2014) outlines five different forms of theory, including analysis, explanation, prediction, explaining and predicting, and design and action [20]. Riedl & Léger (2016) propose a taxonomy of neuroscience theories based on three categories: analysis, explanation, and design and action. They argue that reference theories from neuroscience and related disciplines can be classified into one of these categories, although overlapping can occur. The three theory types are interdependent, with explanation relying on analysis, and design and action benefiting from explanation. The authors also discuss the importance of theoretical neuroscience knowledge for NeuroIS scholars [4].

The review of published articles indicates that 55% of NeuroIS articles have utilized the Explanation theory, 29% have incorporated the Design and Action theory, and 16% have applied the Analysis theory (Figure7).

The Explanation theory is the most commonly utilized theory in NeuroIS research, suggesting that researchers are primarily focused on understanding the underlying mechanisms and processes of neurological phenomena in information systems. The Design and Action theory, which focuses on the practical application of neuroscientific findings in designing and implementing information systems, is also a popular choice among researchers. The Analysis theory, which emphasizes the use of neuroscientific methods to analyze and interpret data in information systems research, is less commonly used but still present in a significant number of articles.

Overall, these findings suggest that NeuroIS researchers are interested in a wide range of theoretical approaches and methodologies, reflecting the interdisciplinary nature of the field. By incorporating multiple theories and perspectives, researchers can gain a more comprehensive understanding of how neuroscience can inform and improve information systems design and implementation. See Table 3 and Figure 7. (In this section, the review articles that discussed and expressed the general definition of neurois were removed and only 221 articles were reviewed.)

Table 3. Theory type in NeuroIS

Theory type	***Attributes***	***Studies***
NeuroIS Theory-Analysis	Neuroscience theories in the analysis category provide descriptions and classifications of neuroscience phenomena, including the fundamentals about the anatomy of the nervous system, such as the structure and function of neurons and the organization of the human brain into four lobes. This descriptive knowledge is important for gaining insight into the hierarchical relationships between various anatomical regions from a NeuroIS perspective [4].	35
NeuroIS Theory - Explanation	In recent years, it has become clear that the brain functions as a network with many connections. Both gut feelings (emotion) and logical thinking have distinct neural structures in the human brain. Certain mental processes rely on activity in specific brain regions, and impairments in these areas can lead to cognitive, emotional, or behavioral problems. NeuroIS scholars must understand neuroscience terminology, brain region interconnections, and the roles of specific brain areas and nervous system components. This knowledge is essential for understanding cognitive, emotional, and behavioral functions, as well as for developing theoretical knowledge. Another important area of theoretical knowledge is the basal ganglia, which are subcortical brain regions that are important for functions like motor control, reward processing, learning, and motivation. Contemporary NeuroIS research often does not incorporate neuroscience theories, but applying these theories can lead to creative insights and provide a framework for decision making and the influence of emotion on it [4].	121
NeuroIS Theory – Design and Action	Neuroscience theories are used to create guidelines for building neuro-adaptive systems. Design science research in the information systems field focuses on developing theories for creating IT artifacts with specific purposes. One major application strategy involves integrating neuroscience tools into IT artifacts. The goal is to develop prescriptions for designing neuro-adaptive systems that can be used by engineers and researchers for developing saleable systems and prototypes [21].	65

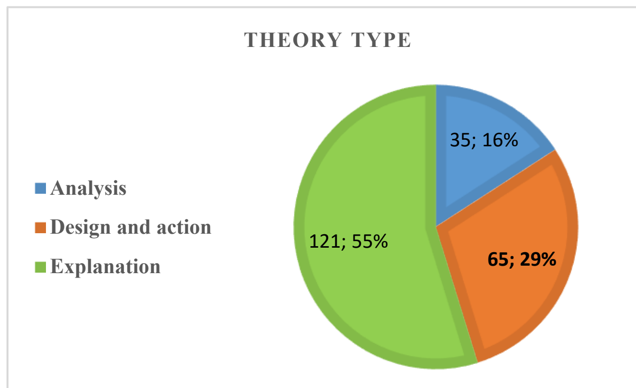

Figure 7. Articles published based on theory type in NeuroIS (N=221)

7- The Direction of the Primary Subjects (Constructs) of NeuroIS Research

A study of theoretical research by, Pavlou, Davis and Dimoka (2007) revealed that NeuroIS candidate topics can be categorized into four groups. This list adds to existing literature on NeuroIS topics and emphasizes the potential of IS and neuroscience research in various areas. The structures are grouped into four categories as follows (Table 4) [22]. Cognitive processes, emotional processes, social processes, and decision-making processes. These factors reflect how individuals comprehend, feel about, engage with others, and make decisions regarding objective things. Figure 8 illustrates the predominant thematic focus among the 244 papers analyzed, with a notable emphasis on cognitive processes (105 papers, 43%) and emotional processes (60 papers, 25%). In contrast, social processes

(45 papers, 18%) and decision-making processes (34 papers, 14%) have received comparatively less attention. It is noteworthy that cognition and emotion play integral roles in both social interactions and decision-making. These findings suggest that the NeuroIS community has primarily delved into the fundamental processes while leaving a gap in exploring their implications for social dynamics and decision-making paradigms. Moving forward, future research in the field of NeuroIS could benefit from a more balanced exploration of all four organism factors to gain a comprehensive understanding of how cognitive, emotional, social, and decision-making processes interact and influence each other within the context of information systems. By bridging the gap between fundamental processes and their implications for social dynamics and decision-making paradigms, researchers can contribute valuable insights that may enhance the design and implementation of information systems to better support human cognition, emotion, social interactions, and decision-making processes.

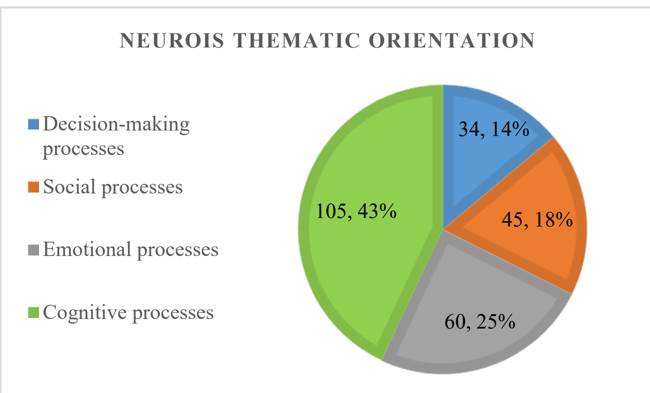

Figure 8. Articles published based on constructs of NeuroIS research (N=244)

8- Analysis of Methodological of NeuroIS Researches

Based on an extensive review of pertinent literature (comprising 244 papers), the research methodologies were meticulously categorized and synthesized, as illustrated in Figure 9. Concerning the research methodologies employed, a significant portion of the papers (136 articles in total) within this study utilized an experimental design, while 21 studies opted for survey methodologies, and 49 papers adopted mixed research methodologies.

It is evident that studies utilizing mixed research methodologies are relatively new, suggesting that mixed research could potentially emerge as a novel trend within the NeuroIS domain. In the realm of mixed studies, Zazon et al. in 2023 employed a mixed-research framework, amalgamating a neuro-based decision support system to stratify cognitive functions into distinct levels aimed at enhancing candidate information during recruitment processes [35]. Their methodology involved evaluating the functional and cognitive proficiencies of 142 adults through assessments of executive functions and intelligence scores. Subsequently, brain signals were analyzed using EEG technology, and machine learning algorithms were leveraged to classify executive functions and intelligence levels.

Table 4. Constructs of NeuroIS research

constructs	***Attributes***	***Topics***
Cognitive processes	NeuroIS research focuses on cognitive processes and their impact on information systems (IS). It encompasses five main areas: enhancing task performance [23], understanding ability to uncover the cognitive neural mechanisms of individuals, particularly in areas such as attention distribution [24], addressing security challenges [14] [15], improving user experience, and using neuroscience to comprehend IS adoption [25] .Researchers use objective tools to overcome biases and gain a better understanding of human-computer interaction.	Information processing, Cognitive effort, Working memory, Multitasking; Automaticity; Habit; Priming; Spatial cognition; Flow
Emotional processes	Emotion is crucial in human experiences; NeuroIS offers new ways to understand emotions. Researchers focus on enhancing user experience [26], integrating emotions into IS design, and exploring emotional processes in IS use. Studies cover topics like screen luminance impact on visual fatigue [27], emotion-inducing images for information recall [28], and avatar similarity on emotional regulation [29]. Technostress in IS can negatively affect job satisfaction and organizational commitment. Human emotions are important in IS security and adoption studies, influencing loyalty to a website [30].	Pleasure/enjoyment, Displeasure, Happiness, Sadness, Anxiety, Disgust, Fear, Anger, Emotional processing
Social processes	NeuroIS research has identified four key constructs related to social processes: trust, inspiration, distrust, and mentalizing. Trust in IS and IS adoption have been the primary focus within this category [31] [32].	Social cognition, Trust, Cooperation, Competition, Theory of mind
Decision-making processes	New technologies such as data analytics can be helpful for decision makers, but they will not completely replace traditional decision-making processes. There is a lack of research on information systems security and trust. NeuroIS researchers have used EEG and other methods to study	Calculation, Uncertainty, Risk, ambiguity, Loss, Rewards and utility, Intentions,

	individual decision-making and predict security behavior [33], as well as the relationship between decision-making and trust. For instance, studies have found that product ratings and sales volume can impact consumers' trust in products [34]	Task intentions, Motor intentions

Similarly, Reßing et al. (2022) conducted a study on mind wandering in the context of digital technology utilization [36]. Their research entailed an experimental approach integrating EEG, eye-tracking, questionnaires, and performance metrics to evaluate mind wandering occurrences. The study encompassed the collection of quantitative data through self-reported assessments of mind-wandering frequency and duration, alongside objective appraisals of task performance. Additionally, qualitative data were gathered through semi-structured interviews with participants to offer a more comprehensive understanding of their experiences with mind wandering during digital technology usage.

Moreover, 38 studies centered on literature reviews were undertaken for this research endeavor. These literature reviews, characterized by their substantial citations and influence, partly reflect the evolving emphasis within the NeuroIS domain on embracing and integrating such research methodologies in recent years.

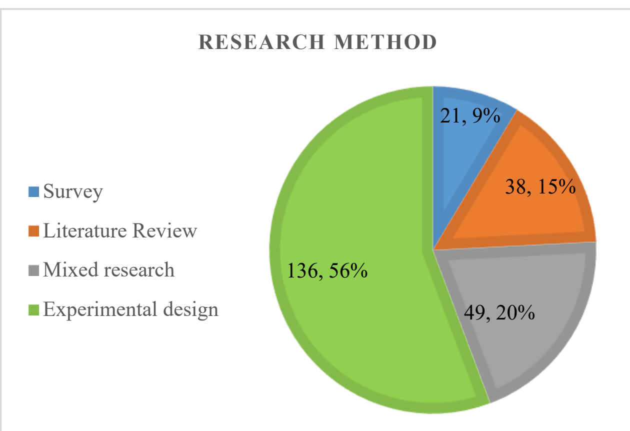

Figure 9. Methodology of published researches in NeuroIS fields (N=244)

9- Analysis of Areas of NeuroIS Researches

Vom Brocke et al. (2020) identified key domains in NeuroIS such as IS design, IS utilization, emotion research, and neuro-adaptive systems [36]. It is crucial for NeuroIS to enhance its impact on practical situations. Following calls for addressing societal and economic challenges in the IS domain, NeuroIS should increase its involvement to address such issues more directly. NeuroIS research should demonstrate how utilizing neuroscience knowledge and methods can offer unique insights [38].

9-1- Information Systems Design (IS Design)

Significant opportunities exist for new research in the synergy between NeuroIS and design [36]. Neuroscience research informs cognitive and affective functions in design processes. It explores problem structuring, novelty production, refinement management, and consensus achievement. Future NeuroIS research aims to enhance IS design and evaluation through neurophysiological insights. Key challenges include understanding complex problems, defining good artifacts, and exploring diverse design approaches. Evaluating includes defining goodness criteria, selecting evaluation methods, and analyzing results to define contributions and evaluate user experience [36]. Contributions to design artifacts and design theory are essential. Integrating NeuroIS with DSR can inform the design of IS artifacts and build neuro-adaptive IS artifacts. Neuroscience can inform IT artifact design and evaluation without using neuroscience methods. Biological processes can design adaptive systems for positive outcomes. Biofeedback systems can help users control physiological indicators for better outcomes. Electrophysiological brain function measures can replace input devices in human-computer interaction for improved outcomes [4].

9-2- Information Systems Use (IS Use)

Research on the negative consequences of digital communication and Internet use is crucial. Normal interpersonal communication could diminish rapidly due to excessive IT use. Smart devices, while enhancing our lives, can also hinder social interactions and productivity [36]. Cyber security, where time pressure is significant, is one area affected. Overuse of IT harms face-to-face communication and social connections [39]. Despite evidence of negative impacts, stakeholders overlook well-being concerns. NeuroIS research can guide discussions on mitigating these effects. IS community plays a vital role in promoting healthy communication amidst technological advancements. NeuroIS can address key research questions to improve understanding and mitigate adverse effects of digital communication devices. NeuroIS research can delve into the neurological processes involved in achieving communication goals. Can digital devices mimic non-verbal cues effectively? Does excessive digital communication hinder social development? Emojis in digital communication may not fully replace real emotions [40].

9-3- Emotion Research

It's crucial to improve communication by defining emotion-related concepts concisely. NeuroIS, as a dynamic field, can redefine emotion more effectively than traditional emotion research. Walla (2018) provides a comprehensive understanding on how cognitive processing (e.g. language) is separate from affective processing that can lead to emotions [39]. Emotions are expressed through measurable behaviors, such as facial expressions, reflecting underlying affective processes. Objective measures are essential to understand the neural activity that drives behavioral responses in using IT systems. Emotion research in NeuroIS faces challenges in integrating self-report measures with physiological responses to predict human behavior accurately. The interplay of preference, technology acceptance, and affective processes underscores the importance of a multi-method approach in research [36].

9-4- Neuro-Adaptive Systems

Neuro-adaptive systems can enhance user experience by responding to their emotional and cognitive states. These systems, like biofeedback bracelets, use body data to adjust smartphone applications. Research on neuro-adaptive systems emphasizes the importance of considering affective computing literature. These systems aim to improve human-computer interaction, potentially benefiting various aspects of society. They could act as personal assistants for healthier lifestyles and contribute to evidence-based medicine. Despite their research potential, their practical implications are not well-documented in academic literature productivity [36].
Figure 10 displays the main areas of focus from the analysis of 244 papers. Among these, 46% of the articles, totaling 112, focus on the utilization of information systems, making it the most extensive domain in NeuroIS research. Information systems design follows closely with 59 articles (24%), emotions with 41 articles (17%), and adaptive-neural systems with 30 articles (13%).The extensive body of work in NeuroIS highlights a significant focus on information systems. This exploration underscores the crucial role of information systems in various contexts. The research emphasizes the complexities of utilizing information systems and the importance of designing efficient, effective, and user-friendly systems. NeuroIS studies on emotions and adaptive-neural systems demonstrate a comprehensive approach to advancing knowledge in these areas.

10- Disruptive Technologies and Tools in NeuroIS Research

There are several tools and Disruptive technologies that are commonly used in NeuroIS research to study the intersection of neuroscience and information systems. Disruptive technologies are innovative technologies that fundamentally change the way things are done, often leading to the disruption of existing industries or practices.

In the field of NeuroIS research, several disruptive technologies have been used to advance our understanding of how the brain interacts with information systems. These disruptive technologies are transforming the field of NeuroIS research by providing new ways to study the brain's interaction with information systems and technologies. They offer exciting opportunities for researchers to explore the complex relationship between the brain, behavior, and technology in innovative and impactful ways. Some examples of disruptive technologies and key tools utilized in NeuroIS research are outlined in Table 5 and Figure 11.

Table 5: Disruptive technologies in NeuroIS research

Technology	***Attributes***
Brain-Computer Interfaces (BCIs)	BCIs are devices that enable direct communication between the brain and external devices, such as computers or prosthetic limbs. In NeuroIS research, BCIs are used to study how users can control information systems using their brain activity. (Examples: [41] [42]).
Virtual Reality (VR) and Augmented Reality (AR)	VR and AR technologies create immersive environments that can be used to study user interactions with information systems in a more realistic and engaging way. These technologies have the potential to revolutionize the way we study user behavior and cognition in the context of information systems. (Examples: [43] [44]).
Wearable Devices	Wearable devices such as smart watches, fitness trackers, and EEG headsets can collect real-time data on users' physiological responses and brain activity. These devices are increasingly being used in NeuroIS research to study user engagement, emotions, and cognitive processes. (Examples: [45] [46] [47] [48] [49]).
Artificial Intelligence (AI) and Machine Learning	AI and machine learning algorithms are used in NeuroIS research to analyze large datasets of brain activity and behavioral data. These technologies can help researchers identify patterns and relationships in the data that may not be apparent through traditional analysis methods. (Examples: [50] [51]).
Robotics	Robotics technology can be used in NeuroIS research to create interactive systems that respond to users' brain activity or emotional states. Robots can be programmed to adapt their behavior based on the user's cognitive and emotional responses, leading to more personalized and engaging interactions. (Examples: [2] [52])
Neurofeedback	Neurofeedback is a disruptive technology that uses real-time brain activity data to provide feedback to users, allowing them to learn to control their brain activity. In NeuroIS research, Neurofeedback can be used to study how users can improve their cognitive performance and well-being through brain training exercises. (Examples: [35] [53]).

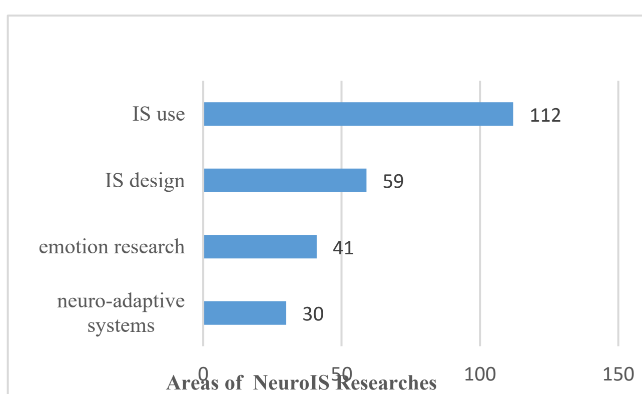

Figure 10. Articles published based on Areas of NeuroIS Researches (N=244)

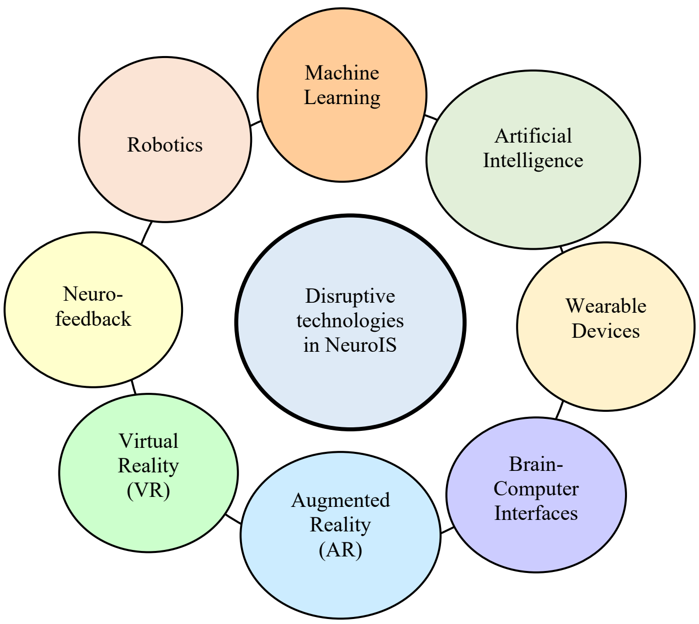

Figure 11. Disruptive technologies in NeuroIS research (Source: authors)

Table 6: key Tools in NeuroIS research

Tools	***Attributes***
Functional Magnetic Resonance Imaging (fMRI)	FMRI is a neuroimaging technique that measures brain activity by detecting changes in blood flow. It is commonly used in NeuroIS research to study how the brain responds to different information systems and technologies. (Examples: [54] [55]).
Electroencephalography (EEG)	EEG is a non-invasive technique that measures electrical activity in the brain. It is often used in NeuroIS research to study cognitive processes such as attention, memory, and decision-making. (Examples: [56] [57] [58]).
Event-related potential (ERP)	ERP is a method used in neuroscience and neuroimaging to measure brain activity in response to specific events or stimuli. By measuring brain activity in real-time, researchers can better understand cognitive processes, attention, memory, and emotional responses during information processing tasks. (Examples: [59] [60]).
Eye-tracking (ET)	Eye-tracking technology is used to monitor and record eye movements and gaze patterns. It is frequently used in NeuroIS research to study how users interact with information systems and websites. (Examples: [61] [62] [63]).
Eye-fixation related potential (EFRP)	EFRP studies brain activity when eyes fixate on visual stimuli. In NeuroIS, EFRP explores how brain processes visuals and links to cognitive/behavioral responses. Researchers use EFRP to understand how people perceive/process visual stimuli, like websites, ads, or interfaces, to improve design for better user experience. (Examples: [64] [65]).
Galvanic Skin Response (GSR)	GSR measures changes in skin conductance, which can be an indicator of emotional arousal and stress. It is often used in NeuroIS research to study user emotions and reactions to information systems. (Examples: [66] [67]).
Magneto encephalography (MEG)	MEG is a neuroimaging technique that measures magnetic fields produced by the brain's electrical activity. It provides high temporal and spatial resolution, making it useful for studying fast neural processes related to technology use. (Examples: [68] [69].
Functional near-infrared spectroscopy (fNIRS)	FNIRS is a non-invasive technique that measures changes in blood oxygenation in the brain, providing information about brain activity during cognitive tasks. It is often used in studies of attention, memory, and decision-making in relation to technology. (Examples: [13] [70]).
Electrodermal activity (EDA)	Electrodermal activity (EDA) measures skin conductance changes in response to emotions or stress. In NeuroIS, EDA studies emotional and cognitive responses to technology. Researchers use EDA to assess user arousal and engagement with digital interfaces, providing insights into user experience and technology engagement. (Examples: [71] [72]).
Automatic Facial Expression Analysis (AFEA)	AFEA involves the use of computer algorithms to detect and analyze facial expressions in real-time, allowing researchers to understand how individuals react to various stimuli in a more objective and reliable manner. (Examples: [73] [74]).
Heart Rate Variability (HRV)	HRV measures the variation in time intervals between heartbeats, reflecting the autonomic nervous system's activity. It is used to study stress, arousal, and emotional responses to technology. (Examples: [46] [47] [48] [75]).
Electrocardiogram (ECG or EKG)	ECG is a tool used to measure the electrical activity of the heart. ECG provides information about heart rate, heart rate variability, and other cardiac parameters that can reflect the emotional and cognitive states of users during their interactions with technology. (Examples: [76] [77]).
Genetics	Genetics research in NeuroIS can also help identify genetic markers that may predict an individual's response to different neurotechnologies, such as brain-computer interfaces or neurofeedback. This personalized approach to neurotechnology can enhance the effectiveness of interventions and improve outcomes for individuals with neurological conditions. (Examples: [78] [79]).
Experimental design and statistical analysis	Rigorous experimental design and statistical analysis are essential tools in NeuroIS research to ensure the validity and reliability of research findings. (Examples: [80] [81])).

NeuroIS software tools	There are also specialized software tools and platforms available for conducting NeuroIS research, such as BrainVision Analyzer, EEGLAB, and NeuroPype. These tools help researchers analyze and visualize brain activity data and integrate it with behavioral data from information systems. (Examples: [82] [83] [84]).

Based on our sample comprising 244 instances, Figure 12 illustrates that Electroencephalography (EEG) is the predominant tool utilized in NeuroIS research, accounting for 42 papers or 29%. This is followed by eye-tracking (ET) and Functional Magnetic Resonance Imaging (FMRI), each represented in 39 papers, equivalent to 16%, and Heart Rate Variability (HRV) with 33 papers, constituting 14% of the total. Additionally, the assessment of Functional near-infrared spectroscopy (fNIRS) is observed in 11 papers (5%), Electrodermal activity (EDA) and Event-related potential (ERP) each appear in 9 papers, representing 4% each. Other methodologies and tools applied in NeuroIS encompass Electrocardiogram (ECG or EKG), Automatic Facial Expression Analysis (AFEA), Genetics, Magneto encephalography (MEG), Galvanic Skin Response (GSR), and Eye-fixation related potential (EFRP).In terms of future research directions, it would be beneficial to explore the integration of multiple neuroimaging techniques to gain a more comprehensive understanding of brain activity in the context of information systems. Moreover, investigating the combination of physiological measures with neuroimaging data could provide valuable insights into the cognitive processes underlying human-computer interactions. Additionally, exploring the potential applications of emerging technologies such as virtual reality and brain-computer interfaces in NeuroIS research could open up new avenues for studying the interplay between technology and the human brain. Overall, continued advancements in neuroimaging technology and interdisciplinary collaborations are crucial for advancing the field of NeuroIS and unlocking its full potential in understanding human cognition and behavior in the digital age**.**

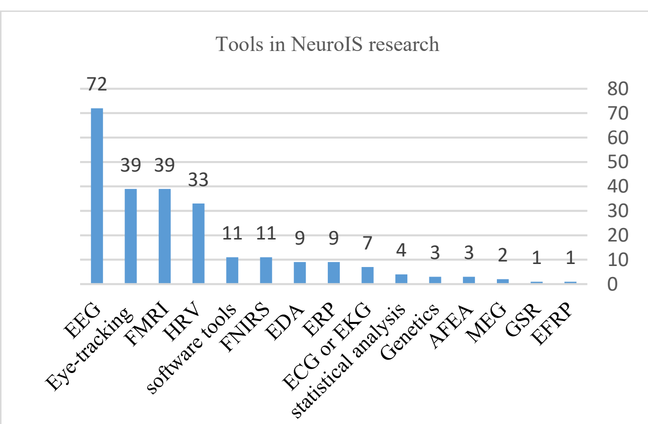

Figure 12. Articles published based on Areas of NeuroIS Researches (N=244)

11- Conclusions

NeuroIS is an emerging field with a limited number of studies. This paper aims to provide a state-of-the-art overview of NeuroIS by focusing on 244 articles extracted from the Scopus database. It discusses the development and application prospects of NeuroIS, covering its origins, the integration of neuroscience and information systems, relevant publications, contributions of neuroscience to IS research, thematic orientation of NeuroIS research, methodological analysis of NeuroIS research, areas of NeuroIS research, and disruptive technologies and tools in NeuroIS research. Recent research indicates rapid evolution in NeuroIS, offering valuable insights into the intersection of neuroscience and information systems. This field has the potential to revolutionize user behavior understanding, system design, and decision-making processes, paving the way for innovative applications and advancements in information systems.

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Journal of Information Systems and Telecommunication
Vol.13, No.2, April-June 2025, 154-164

http://jist.acecr.org
ISSN 2322-1437 / EISSN:2345-2773

Credit Risk Prediction: An Application of Federated Learning

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Received: 27 Dec 2024/ Revised: 04 Jun 2025/ Accepted: 19 Jul 2025

Abstract

Credit risk is one of the major challenges faced by all financial institutions. Different institutions apply various techniques and models to reduce the risks associated with lending and other financial activities. However, due to the sensitivity of financial data and the diversity of modeling approaches, sharing data among institutions is extremely difficult, often impossible. As a result, improvements in credit risk prediction models typically occur in isolation, hindering collective progress toward higher accuracy and broader effectiveness. Federated learning offers a promising solution by allowing institutions to collaboratively train models without exposing or transferring sensitive data. In this research, we present a federated learning architecture for credit risk prediction that ensures privacy throughout the entire training process. Our results indicate that this approach not only protects data confidentiality but also maintains high predictive accuracy over numerous training rounds, offering a reliable and efficient framework for institutional adoption. The core contribution of this work is the development of a decentralized federated learning (FL) architecture tailored to heterogeneous, non-IID financial data. This framework enhances privacy, scalability, and regulatory compliance, and demonstrates performance advantages over traditional methods. In this article, we demonstrate that using five real-world credit risk datasets, the decentralized FL architecture significantly improves model accuracy (ranging from 71% to 99%) compared to traditional machine learning methods, especially in scenarios where privacy and communication efficiency are essential. While centralized FL achieves the highest average accuracy (up to 83%), the decentralized model provides a strong trade-off between performance and privacy-aware collaboration.

Keywords: Federated Learning (FL); Credit Risks; Financial Institutions; Heterogeneous Data; Decentralized Federated Learning (DFL) Architecture.

1- Introduction

Credit risk is among the major risks which are associated with commercial banks and other financial institutions. It refers to the probability of default in the repayment of the principal amount along with interest on loans, which may adversely affect organizational performance and, in fact, the economy as a whole [22]. The forecast of credit risk has become indispensable in general, and within financial industries in particular, as a result of the insightful support it gives to the organizational decision-making processes enabling the organizations to avoid potential losses [29].
However, despite the importance of credit risk prediction, existing methods often fail to address the unique challenges of financial institutions, such as the need for secure data sharing, managing heterogeneous and non-IID (non-independent and identically distributed) data, and fostering collaboration without compromising privacy. With the development of data-driven technologies, machine learning has attracted increasing interest in credit risk prediction. However, most machine learning models collect and process data in the centralized server, which might bring serious security leakage and privacy violation problems [5]. Moreover, the reluctance of organizations to share sensitive data for model training due to privacy and security concerns further complicates the collaboration needed for accurate predictions.
Therefore, Google, in the year 2016, proposed a more recent AI-based technology known as federated learning [29]. Instead of the sharing of local data, federated learning secures sensitive data by sharing local models. This is

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helpful when organizations want to train larger datasets but cannot share data due to legal, strategic, or economic reasons. Federated learning can, therefore, enable different organizations to collaborate without sharing data with full security and privacy assurance of the data through decentralized models [29].

Despite the promise of federated learning, existing FL models whether centralized or decentralized often struggle with the specific challenges faced by financial institutions, such as the management of heterogeneous, non-IID data distributions and ensuring robust privacy protections. This article proposes a decentralized architecture for heterogeneous data environments to predict credit risk using federated learning, addressing these challenges more effectively than current methods.

The main contributions of this paper are as follows:

1- A novel decentralized federated learning architecture is proposed for credit risk prediction using heterogeneous, non-IID financial datasets, eliminating reliance on a central server.
2- Implementation of a socket-based communication framework to simulate real-world decentralized environments and facilitate peer-to-peer model aggregation.
3- Experimental evaluation on five real-world credit datasets, comparing traditional machine learning, centralized FL, and decentralized FL approaches across multiple performance metrics.
4- Discussion of accuracy, scalability, and privacy trade-offs, with results showing decentralized FL achieves competitive accuracy (71%–99%) while enhancing data privacy and reducing central dependency.

2- Literature Review

2-1- Credit Risk

Risks might have serious and sometimes unpredictable consequences on organizations, banks, companies, or even the wider economy. Credit scoring is used to evaluate credit risk prediction, which involves quantifying the probability of future default. Credit scoring methods can be divided into two categories: judgmental and operational scoring. While Judgmental scoring systems are based on specific customer attributes, and the scores are assigned accordingly. In contrast, in operational scoring systems, much emphasis is placed on predictive models of financial variables [22].

For instance, a judgmental scoring could be the 5C criterion adopted by banks, which entails [11],[14]:

Character: past activities, personal credit;
Capacity: income capacity;
Capital: the financial statement evaluation of the individual;
Coverage: the assets given to institutions for coverage purposes during credit issuance;
Conditions.

Therefore, the other criteria for judgmental scoring include the LAPP method which includes: Liquidity; Activity; Profitability; Potential [11],[14].

Operational scoring techniques rely more on quantitative analysis for predicting credit risk, employing models and techniques such as mathematical programming, nearest neighbor algorithms, artificial neural networks, genetic algorithms, etc. [27],[15],[17]. The following table, Table 1, summarizes some of these.

Table 1: Credit scoring methods in credit risk

Scoring Methods	Criteria	Sources
judgmental scoring	5C	Rouintan, P., 2006
	LAPP	
Operational scoring	mathematical programming	Rasouli, M., 2022
	nearest neighbor algorithms	
	ANN	
	genetic algorithms	

2-2- Machine Learning & Federated Learning

The most salient uses include finance, health, transportation, and e-commerce. Considering the popularity that machine learning has gained, much attention must be paid to privacy in data and security. Traditional machine learning methods use a centralized approach in model training by collecting training data on a central server. Data gathering on a central server remains one of the biggest challenges in machine learning when sensitive information exists and causes quite several security threats to data privacy [21].

This prompted Google in 2016 to introduce a new technology in artificial intelligence called Federated Learning. As opposed to the sharing of local data, federated learning protects sensitive data by sharing local models. The decentralized approach to model training will be the technique. It will be very useful in cases where various regions want to train models on larger datasets than their own, but due to legal, strategic, or economic reasons, sharing the data with others cannot be done. According to the definition of machine learning. Federated Learning is a framework where a global model is designed in advance to solve collaboration problems among data owners without data exchange. The central server aggregates optimized models from all regions. Since no data is being exchanged, there is no risk of exposure to user privacy. Various sections or regions in a federated learning system send their own trained models to a center server. Further, this training may be iterated until a satisfactory level of accuracy is achieved [29].

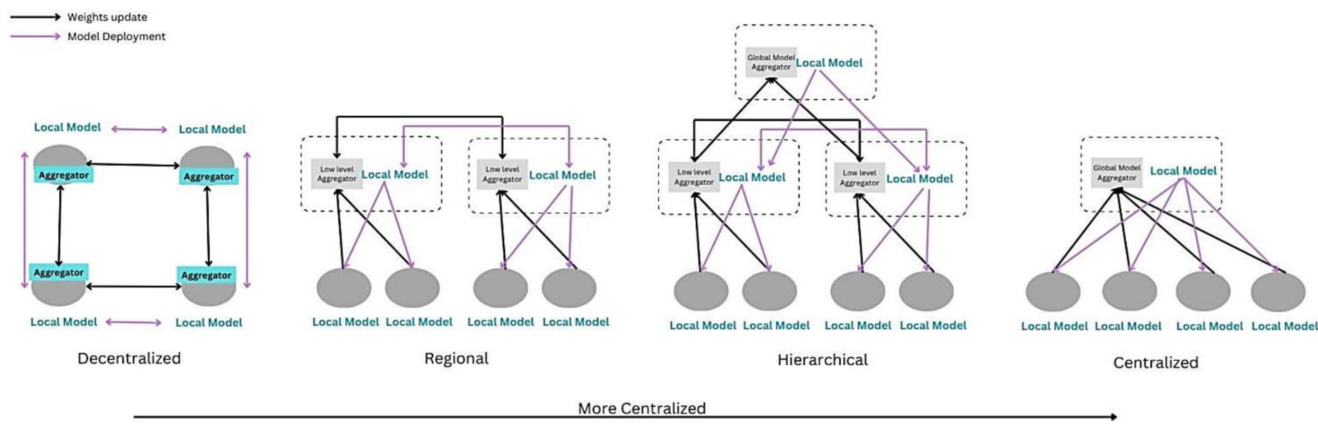

Fig. 1 Application of FL

After having given a view on what Federated Learning is, we go further into the significant benefits of federated learning against traditional centralized machine learning methods in more detail [6]:

Data Security: The training datasets remain on the devices, hence there is no need for a centralized dataset.

Data Diversity: Allows access to heterogeneous data when the sources of data can only communicate their data at certain times.

Continuous Real-time Learning: Models keep improving continuously with customer data without gathering the data for continuous learning.

Hardware Efficiency: It deploys less complex hardware as the models in federated learning do not require a high-end central server for data analysis.

Federated learning is widely applicable in numerous fields such as finance, healthcare, and transportation, positioning it as a transformative technology in our data-driven world [6],[7]. This article will concentrate on one of its primary uses in the financial sector: credit risk predictions, which will be elaborated on in the next section. Figure 1 illustrates the various applications of federated learning.

2-3- Federated Learning in Credit Risk Prediction

Given the various methods for predicting credit risk discussed in previous sections, each technique has its own set of advantages. However, when organizations want to enhance their model performance through data sharing but face challenges due to the sensitive nature of financial information, federated learning emerges as a viable solution. This approach enables two or more financial institutions to improve their model performance without sharing actual data. Federated learning functions as a decentralized method, allowing collaborating organizations to refine their models by exchanging model parameters rather than data on a centralized server [2]. Research studies in this area are summarized in Table 2.

The first article introduces FedKT, a federated learning framework designed to enhance credit scoring while ensuring data privacy. However, the study falls short in providing adequate comparative analysis among different machine learning methods, leaving a gap in understanding its relative effectiveness and does not address how federated learning can handle heterogeneous and non-IID data distributions commonly found in financial contexts [26].

The second article investigates the use of federated learning for mortgage credit risk assessment, with a focus on the Freddie Mac dataset. While there are promising advancements for smaller financial institutions, the research is constrained by its narrow focus on a specific dataset and the examination of only loans with a final status. These limitations hinder the generalizability of the findings to wider contexts. Additionally, the study lacks a comprehensive comparison between centralized, decentralized, and federated learning approaches, which leaves out critical insights on the relative performance and scalability of these methods. There is also a lack of comparisons between centralized and decentralized architectures, as well as other federated learning methods, which could have enriched the research [9].

The third article delves into federated learning paired with the SecureBoost algorithm for credit evaluation among micro and small enterprises (MSEs). This approach effectively tackles privacy issues and data silo challenges, resulting in enhanced accuracy and stability. Furthermore, the study mainly depends on two external data sources (credit and electricity consumption data) and does not consider other potentially relevant datasets, limiting the model's applicability across various contexts. Moreover, this study does not explore the impact of non-IID data and lacks an in-depth analysis of the performance across different federated learning architectures. [27].

All the mentioned articles share a common limitation: they lack a thorough comparison of the three approaches centralized, decentralized, and federated learning.

Furthermore, they depend on a narrow range of machine learning methods for their comparisons, and some studies use smaller, more homogeneous datasets. These gaps highlight the need for a more comprehensive and scalable solution that can handle heterogeneous, non-IID data, and provide a better understanding of the comparative performance across different architectures. In general, research in this area is limited and still in its early stages, with no substantial work done in Iran so far.

Table 2: Papers in credit risk prediction using federated learning

Title	Source
A novel federated learning approach with knowledge transfer for credit scoring	Zhongyi Wang et al., 2024
Federated Learning for Credit Risk Assessment	Chul Min Lee et al., 2023
MSEs Credit Risk Assessment Model Based on Federated Learning and Feature Selection	Zhanyang Xu et al., 2023

3- Methodology

3-1- Dataset

In credit risk assessment and prediction, several factors can affect a borrowers' ability to repay their debts. These factors help financial institutions estimate the likelihood of repayment. Common features used to evaluate credit risk include:
Demographic Characteristics: Information such as age, gender, marital status, and education level, which aid in analyzing the borrower's profile.
Financial Characteristics: This encompasses income, employment status and history, debt-to-income ratio, current financial obligations, and levels of savings and assets.
Loan-Specific Features: Factors such as loan amount, term, interest rate, and purpose relate to the specific conditions of the loan granted.
These features may vary based on the policies of different institutions and are sometimes combined to create a more accurate evaluation of the borrower's overall risk. In this Fig. 1 Applications of FL study, open-source data from various institutions will be utilized to develop an effective model in the field of credit risk:
The Univ.AI Hackathon dataset includes demographic details of loan applicants, such as age, income, job experience, and marital status. It is a binary-class dataset(0 and 1) with no missing values, comprising around 252,000 records [19].
The Loan Data from 2007 to 2015 features issued loans along with financial attributes like loan amount and interest rate. This dataset contains 73 features and approximately 855,000 records, though some values are missing [12].
The German Credit Card dataset emphasizes credit history and personal information, consisting of 21 features and 1,000 records, with no missing values [1].
The Credit Risk dataset encompasses features such as age, income, loan amount, and loan status. It is a binary-class dataset with 12 features and 32,000 records [8].
The Credit Risks dataset includes payment history and credit-related details, such as payment delays and the number of bank accounts. It has 28 features and around 100,000 records, is categorized into three classes (good, bad, standard), and contains some missing values [16].
Finally, it has been tried to use different datasets and implement this architecture on these datasets. A summary of the dataset is given in Table 3.

Table 3: Summary of Dataset Features

	Dataset	Features	Records
1	Univ.AI Hackathon Dataset	13	252,000
2	Loan Data (2007 - 2015)	73	855,000
3	Credit Risk Dataset	12	32,000
4	German Credit Card Dataset	21	1,000
5	Credit Risks Dataset	28	100,000

3-2- Research Method

In our research, we collected datasets for credit risk prediction from various sources, each featuring distinct characteristics and exhibiting non-IID (non-independent and non-identically distributed) properties. This indicates that the data originates from different regions, customer segments, or financial contexts, with each dataset presenting its own unique distribution. For instance, one dataset may concentrate on user behavior, while another might focus on economic conditions or credit history, leading to diverse data distributions across the datasets [3]. The non-IID nature poses challenges in federated learning, as the model needs to manage data with differing statistical properties. These variations in data distributions can complicate the federated model's ability to converge effectively or perform well across all datasets. Although these differences mirror the diversity found in real-world credit risk scenarios and can enhance model adaptability, they also bring about complexities such as slower convergence, inconsistent performance, and inefficiencies in resource use. In this study, we have implemented various data preprocessing techniques to mitigate the effects of non-IID data [24],[25]. Since the data across institutions have different characteristics and cannot be combined due to their diverse nature, federated learning can be employed. After identifying the datasets, the next step is to outline the various stages necessary for implementing credit risk prediction using federated learning. The first step involves determining the type of architecture to be used in federated learning. Below, the main types of federated learning architectures are introduced, along with an explanation of the architecture utilized in this research.

3-2-1- Federated Learning Architecture

Federated learning employs various architectures to aggregate and update models. Here, four commonly used architectures are presented [18],[28].

Centralized Architecture
In a centralized architecture, a central federated server manages the training process. Clients send their local model updates to this central server, which aggregates the updates to form a global model. This setup is effective when a limited number of organizations are involved and a high level of trust exists among them.

Decentralized Architecture
The decentralized architecture does not depend on a central federated server. Instead, participating organizations communicate directly with each other or through a decentralized network to share model updates and coordinate training. This architecture is ideal when there is a need to minimize reliance on a central authority or when concerns about the availability or security of a central server arise.

Regional Architecture
In a regional architecture, participating organizations are grouped into zones where local models are trained collaboratively. Model updates from different regions can then be aggregated at a higher level (e.g., a central node for regional updates). This approach is suitable for balancing regional collaboration with national-level cooperation and helps address regional variations in data and needs.

Hierarchical Architecture
In a hierarchical architecture, there are several layers of model aggregation. Local models are combined within subgroups or nodes to produce intermediate-layer models, which are then further combined to create a global model. This structure is ideal for complex organizational frameworks or situations that require multiple layers of collaboration and data sharing.
Figure 2 illustrates these federated learning architectures.
A decentralized architecture is the most appropriate choice for this application. In this model, organizations and institutions function parallel and non-hierarchically while still fostering collaboration. Other architectures depend on a central server, which does not fit the ecosystem of financial institutions. Moreover, the selected datasets indicate that the data cannot be grouped under a central server. Due to the diverse nature of the data, a decentralized architecture seems to be the right option.

3-2-2- Step by Step Procedure

After defining the architecture, the next step involves outlining the procedures for designing a decentralized framework. Each client, represented by different datasets and referred to as clients in federated learning, may employ various methods to train their data, including different machine learning techniques or neural networks.
The general steps include [23],[13]:
1- Local Data Preprocessing
2- Training Local Models
3- Peer-to-Peer Client Communication: Clients exchange model coefficients (gradients of the learning model) rather than raw data.
4- Applying Decentralized Aggregation Methods: This step utilizes decentralized aggregation methods such as averaging or other combination techniques.
5- Establishing Consensus in the Decentralized Learning Process: This involves determining when and among which clients consensus should take place. During the initial phase of training local models, consensus starts with random numbers.

The steps of decentralized architecture illustrated in Figure 3 are as follows:

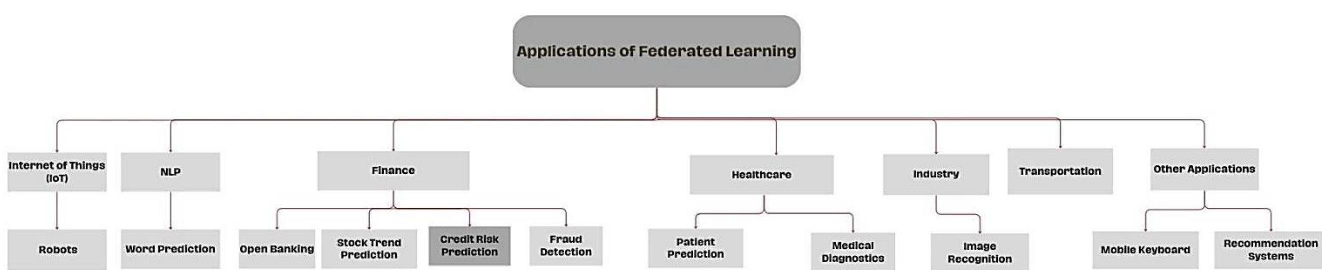

Fig. 2 Federated Learning Architecture [Adapted from 28]

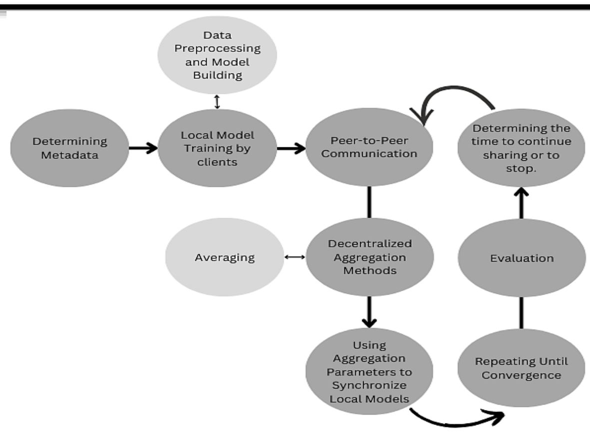

Fig. 3 Steps for designing a decentralized architecture

4- Implementation

The implementation of federated learning is the next significant stage after defining the datasets and architecture. Although federated learning can be accomplished using Python, several specialized frameworks and tools have been developed to assist in the effective execution of federated learning algorithms. These frameworks provide vital building blocks for creating decentralized, privacy-preserving machine-learning models, including federated computation, model aggregation, and privacy-preserving techniques, along with compatibility with established machine-learning libraries. For this study, TensorFlow Federated (TFF) [20] was chosen due to its robust support for federated learning, extensive documentation, and seamless integration with TensorFlow, one of the most widely used machine learning libraries. TFF offers a comprehensive and flexible platform for building federated learning systems, providing key features such as federated computation, model aggregation, and privacy-preserving techniques. These capabilities are essential for implementing decentralized, privacy-preserving machine learning models, particularly in environments where sensitive data cannot be shared.The choice of TensorFlow Federated is also motivated by its close integration with TensorFlow, which allows for a smooth transition from traditional machine learning workflows to federated learning without the need to learn a new framework.Furthermore, TFF's modular design makes it easier to experiment with various federated learning algorithms, which is beneficial for research and practical applications, especially in financial institutions where privacy and data heterogeneity are critical concerns.

However, there are certain limitations faced when using TensorFlow Federated. One challenge is the learning curve associated with setting up the federated learning system, particularly in terms of managing communication between clients and the server, as well as handling the distribution of data. Additionally, although TFF is well-documented, it is still evolving, and certain advanced features may require customization or additional workarounds. Performance optimization for federated learning algorithms in TFF can be complex, particularly when working with large-scale datasets and ensuring efficient resource utilization across distributed environments. Despite these challenges, TensorFlow Federated's comprehensive nature makes it a strong and suitable choice for implementing federated learning in this study. The implementation will follow the process illustrated in Figure 4.

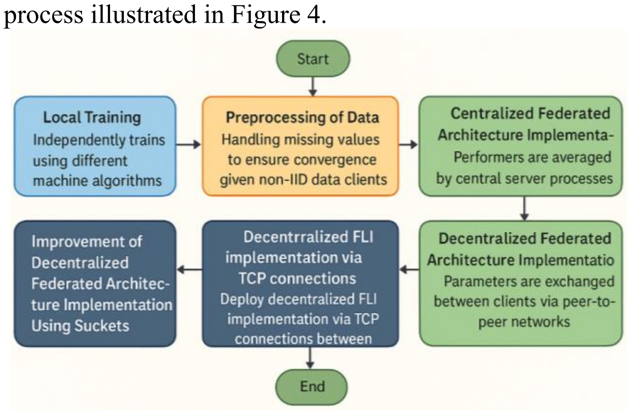

Fig. 4 Steps of Implementing a Decentralized Federated Architecture

4-1- Local Training of Datasets

To initiate our research, we begin by preparing each dataset. This preparation step involves eliminating outliers and handling any incomplete values to enhance the precision and performance of our learning models. We also convert categorical data into numerical values, making it suitable for machine learning algorithms and neural networks. Each dataset undergoes analysis through various methods, incorporating machine learning techniques and neural networks. These different machine learning methods were selected to enable a comprehensive comparison between federated learning and various individual approaches. We implement thorough verification procedures to guarantee the models' reliability and precision. This verification process consists of dividing the data into training and testing sets, developing the models with the training data, and evaluating their effectiveness with the testing data. Following the preparation and individual training phases, we present the models' results in Table 4. This table demonstrates that multiple methods have been implemented across the datasets, enabling a comprehensive comparison between federated learning and various individual steps.

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Table 4: A summary of local dataset models

Dataset	Models	Accuracy
Univ.AI Hackathon Dataset	Gradient Boosting	59 %
Loan Data (2007 - 2015)	Random Forest	99 %
Credit Risk Dataset	MLP	87 %
German Credit Card Dataset	Adaboost	70 %
Credit Risks Dataset	DecisionTree	75 %

These results show significant variation in model performance across datasets, with Random Forest achieving 99% accuracy on Loan Data while Gradient Boosting only reached 59% on the Hackathon Dataset. This variation highlights the importance of selecting appropriate algorithms for specific data characteristics.

4-2- Preprocessing of Datasets

In this section, we selected TensorFlow Federated (TFF) as the platform for implementing federated learning. TFF offers various installation options, encompassing local setups and cloud-based environments like Google Colab. For this research, we selected a local installation, and after encountering some compatibility issues with specific versions, we established Python 3.8.10 as our development environment. Since TFF necessitates datasets to maintain identical numbers of features for model participation, the non-IID (Non-Independent and Identically Distributed) nature of the data required special attention during preprocessing. The datasets were inherently heterogeneous, containing different distributions across clients (organizations), and were often unbalanced with features exhibiting varying importance across clients. To address these challenges, we employed feature selection as a critical preprocessing step. The goal was to eliminate features exhibiting minimal correlation with the target label, as they were deemed insignificant for prediction purposes, especially considering the non-IID nature where some features may be more relevant to certain subsets of data than others.We also incorporated techniques like normalization using MinMaxScaler to ensure consistent feature scaling across all clients, which is crucial for federated learning models to ensure proper model aggregation and convergence. Additionally, we divided the data into training and validation sets, ensuring that the data distribution across these sets remained representative of the real-world non-IID nature. By reducing the feature set to 11 relevant features, we achieved multiple advantages: reduced model complexity, accelerated training times, a decreased risk of overfitting, and improved model interpretability, making the model more manageable and reliable. These 11 features were selected based on their Pearson correlation with the target label, aiming to remove attributes with minimal predictive value. The Pearson correlation coefficient measures the strength and direction of the linear relationship between two variables, making it a suitable choice for identifying features most closely associated with the output. Given the non-IID nature of the data across clients, feature relevance varied, and this method allowed us to retain the most informative features per dataset. Upon completion of preprocessing, the data was transformed into TensorFlow format to be compatible with TFF and was then divided into the necessary training and validation sets. We subsequently designed the federated learning model using Keras, incorporating a Sequential architecture with four Dense layers. The intermediate layers consisted of 32 and 64 nodes with ReLU activation, while the output layer contained a single node with sigmoid activation for binary classification. Finally, we transformed the model into a federated format using TFF, establishing it for implementation in a federated learning environment [4],[10].

4-3- Centralized FL Implementation

It is crucial to define the model and articulate the type of algorithm discussed in previous sections. For this purpose, TFF's federated averaging method within a centralized framework (consistent with the centralized architecture described in Section 2-2) is implemented, which incorporates updates from client models and updates the global model on the server. This process is executed over a fixed number of epochs, established at 50. Each of the five datasets undergoes training, and subsequently, the model is evaluated using test data. The results are presented in Table 5. The assessment results demonstrate that the federated averaging model functions effectively, and in some cases, it even exceeds the performance of models trained independently.

Table 5: The accuracy of centralized federated learning

Accuracy	83 %
Precision	43 %
Recall	49 %
Loss	45 %

The centralized FL achieved a solid 83% accuracy, demonstrating effective model aggregation across diverse datasets. While precision and recall values indicate room for optimization, the model successfully established a baseline for federated learning implementation that can be further improved through hyperparameter tuning.

4-4- Decentralized FL Implementation and Improvement

In the previous centralized architecture, all datasets, formatted in TensorFlow, initiated the training process using the same model definition and random parameters, ultimately leading to convergence. In contrast, the decentralized architecture (as defined in Section 2-2) processes each dataset successively, transferring refined parameters to the next dataset until the model converges, ensuring that each dataset's parameters achieve an optimal learning level. For decentralized implementation, data preprocessing must be completed first. Then, analogous to the centralized architecture, a collaborative learning algorithm particularly distributed averaging is implemented.

The first step involves generating a random parameter using TensorFlow Federated (TFF), which is applied to the first client. Updated parameters are then sequentially passed to the fifth client. Every possible permutation of the five clients is considered, with parameters recalculated for different configurations. However, this method has several drawbacks:

It does not converge, and the model's convergence cannot be detected since each round is treated independently.

This step is time-consuming, as it evaluates all potential configurations, with a single execution taking up to four hours. Due to these limitations, this method was deemed unreliable, prompting the implementation of a second method. The pseudocode of the first step is provided in Algorithm 1.

Algorithm 1: Pseudocode of Decentralized FL in the First Approach

- Generate a random initial model parameter using TFF.
- For each permutation of 5 clients:
  • Set initial state = random parameter.
  • For each client in the permutation:
    ◦ Use client's data to update the model.
    ◦ Pass updated model to the next client.
- Repeat the above for all permutations (5! = 120 total).
- After all updates, evaluate the final model.
- Note: This method does not ensure convergence and is time-consuming, as it explores all possible client orders.

The Second step tackles the convergence issues identified in the first method, we calculate the loss function for all regions after updating each parameter. In the subsequent learning epoch, we select the region with the lowest loss to initiate the process from the strongest region. At each step, we continue to choose the region with the minimum loss until we achieve convergence. For each client, convergence means the model's accuracy stops improving after multiple training rounds and reaches a stable level. However, this step has a limitation: the region with the minimum loss remains unchanged at each step, which hinders the model's ability to converge. The results are presented in Table 6.

According to the table, all regions demonstrate satisfactory learning, except for the fifth dataset. Consequently, a third method has been introduced.

Table 6: Accuracy of Decentralized FL in the Second Approach

Dataset	Accuracy
Univ.AI Hackathon Dataset	63 %
Loan Data (2007 - 2015)	86 %
Credit Risk Dataset	87 %
German Credit Card Dataset	99 %
Credit Risks Dataset	28 %

The third step: After adjusting each parameter for the regions, the loss function for all regions is computed. During the next learning cycle, the minimum loss is chosen to initiate the process from the strongest region. The key difference from Method 2 is that this method begins with the strongest region, and the parameters for each region are refined until convergence is achieved. The results can be found in Table 7 and The pseudocode of the third step is provided in Algorithm 2.

Algorithm 2: Pseudocode of Decentralized FL in the Third Approach

- Initialize the evaluator and model state.
- Define a list to store the loss values for each region.
- Set the round counter to zero.
- While convergence is not reached and the round limit is not exceeded:
  • If it is the first round:
    ◦ For each of the 5 regions:
      ▪ Train the model using the region's training data.
      ▪ Evaluate the model on the region's validation data.
      ▪ Record the loss value.
  • Else:
    ◦ Identify the region with the lowest loss.
    ◦ Train the model on that region's data to update parameters.
    ◦ For each of the remaining regions:
      ▪ Train the model on the region's data.
      ▪ Evaluate and update the corresponding loss value.
  • Increase the round counter by one.
- Once the stopping condition is met (e.g., 10 rounds):
  • Output the final loss values.
  • Output the final evaluation metrics for all regions.

Table 7: Accuracy of Decentralized FL in the Third Approach

Dataset	**Accuracy**
Univ.AI Hackathon Dataset	63 %
Loan Data (2007 - 2015)	87 %
Credit Risk Dataset	87 %
German Credit Card Dataset	99 %
Credit Risks Dataset	28 %

Notably, the fifth dataset performed poorly during the initial training rounds. Instead of using Federated Averaging, this study adopted stochastic gradient descent (SGD) to explore whether it could enhance the learning process in the decentralized architecture. However, the use of SGD did not significantly impact the final model accuracy. Given this, adjustments were made specifically for the fifth dataset.

While the first four datasets represented binary classification problems and learned effectively, the fifth dataset originally contained three classes. To align it with the others and address convergence issues, it was preprocessed into a binary format by combining the "standard" and "good" credit risk categories into a single "good" label. Training was resumed for several rounds under this revised configuration, and the updated results are reported in Table 8.

Table 8: Accuracy of Decentralized FL in the Third Approach after the corrections

Dataset	Accuracy
Univ.AI Hackathon Dataset	71 %
Loan Data (2007 - 2015)	89 %
Credit Risk Dataset	87 %
German Credit Card Dataset	99 %
Credit Risks Dataset	79 %

As can be seen from the table, the results have been considerably improved, proving the effectiveness of Method 3 after the corrections. A new concept is introduced in the next section, more in line with real world applications to which the decentralized architecture must be fitted.

4-5- Decentralized Federated Implementation Using Sockets

After the decentralized architecture of federated learning is implemented, one should know that since all the datasets are kept locally in one environment, this setting is not very realistic. In real-world scenarios, clients are usually not on the same machine and can be distributed across different machines. This way, the problem of communication overhead between the clients arises. The idea of sockets in Python was used to assess whether the usage of more than one machine has any impact on execution time. Sockets serve as an interface for communication where messages can be sent and received across different regions. Each region in this architecture works independently, and after each training phase, it sends its model updates to other regions using sockets. These are then aggregated, using certain algorithms, to enhance the overall model. This cycle continues until the model achieves satisfactory convergence. This step, which leverages the robust capabilities of sockets for managing concurrent and distributed communications, proves to be an effective and efficient method to implement decentralized federated learning. The above steps were first performed for the implementation: all the preprocessing steps were carried out earlier. After that, a sixth intermediary client was used to collect the trained parameters from the regions and send them further to the next regions until convergence. The decentralized federated learning architecture, implemented using sockets, requires approximately 120 seconds. Running on a single machine takes around 90 seconds. In other words, running decentralized federated learning across multiple machines takes 30 more seconds, which is fully expected. Because the socket implementation manages the communication load.

4-6- Results and Discussion

In the previous section, we explored the implementation and examination of federated learning. After choosing the platform and architecture type, the steps involved included data preprocessing, feature selection, and converting the data into TensorFlow format. Initially, we defined the Keras model and adapted it into a federated model. Following that, we implemented centralized federated learning (Section 2-2) using federated averaging and evaluated the results. In the next phase, we tackled the convergence issue by applying three different methods for decentralized federated learning. The third method yielded improved results through specific enhancements. Finally, to simulate real-world conditions and measure communication time, we executed a decentralized implementation using sockets, which facilitated effective communication across various regions. It is important to note that this implementation is not exhaustive. The data volume was not fully representative, and in some cases, the model was not optimized or did not achieve significant progress. While certain methods did not result in improvement, the overall performance was better compared to traditional machine learning approaches. Additionally, further exploration of techniques like averaging could have been beneficial. A summary of the results is provided in Table 9. As summarized in Table 9, traditional machine learning achieves the highest accuracy in certain scenarios, such as loan datasets, but its performance can vary sometimes it even falls short compared to federated learning. On the other hand, decentralized federated learning shows significant improvements over traditional machine learning for specific datasets, like the Hackathon dataset and the German credit card dataset. Generally, centralized federated learning tends to provide the best performance in most situations, primarily due to enhanced data coordination. In some cases, decentralized federated learning can surpass traditional machine learning. This comparison indicates that adopting a federated learning approach can enhance model accuracy in many instances. The best method should be chosen based on the type of data and the model being utilized. One other way to compare is by using confidence interval tests. The confidence intervals used to assess the accuracy of the models are based on the statistical method known as "Interval Estimation." This method typically relies on either the t-student distribution or the normal distribution for its calculations. It determines a range where we expect the true model accuracy to lie. Initially, the models' accuracy is calculated, and then the confidence interval is established using relevant statistical formulas that take into account the data and sample size. The primary metric for these confidence intervals is accuracy, which reflects the proportion of correct predictions to the total predictions.

Depending on the data characteristics, either the normal distribution or the t-student distribution may be applied in this process. In this study, confidence intervals were computed for three distinct models: the Federated Centralized Model, the Federated Decentralized Model, and the Machine Learning Model. The findings reveal that The Federated Centralized Model exhibits a narrow confidence interval (0.83–0.83), indicating high stability and accuracy. In contrast, the Federated Decentralized Model exhibits a broader confidence interval ranging from 0.72 to 0.98, indicating greater variability in its accuracy, with the potential for this model to outperform the others in certain scenarios. The Machine Learning Model also presents a wider confidence interval, spanning from 0.59 to 0.97, which implies that its performance may be less stable. Overall, the results suggest that while centralized federated learning models offer stable and consistent performance, decentralized federated models, despite their higher variability, may still offer potential benefits in certain contexts. Traditional machine learning models, however, may need further refinement to achieve performance stability comparable to federated learning approaches. A summary of the results is provided in Table 10.

Table 9: Comparison of accuracy between MLand FL

Dataset	accuracy	accuracy	accuracy
	Centralized FL	Decentralized FL	ML
Univ.AI Hackathon Dataset		71 %	59 %
			Gradient Boosting
Loan Data (2007 - 2015)		89 %	99 %
			Random Forest
Credit Risk Dataset	83 %	87 %	87 %
			MLP
German Credit Card Dataset		99 %	70 %
			Adaboost
Credit Risks Dataset		79 %	75 %
			DecisionTree

Table 10: Federated vs. Machine Learning: Confidence Intervals and Accuracy

Model	Confidence Interval	Mean Accuracy	Range of Confidence Interval
FL(Centralized)	(0.83, 0.83)	0.830	0.000
FL(Decentralized)	(0.71, 0.99)	0.850	0.280
ML	(0.59, 0.99)	0.790	0.400

5- Conclusion and Research Contribution

This research demonstrates that decentralized federated learning effectively enhances credit risk prediction while preserving data privacy. Centralized FL achieved 83% accuracy with high stability, while decentralized FL showed competitive performance (71%-99%, mean 85%) compared to traditional ML (59%-99%). This study successfully implemented the first decentralized FL framework for credit risk in Iran, with the third iterative approach proving most effective. Socket-based implementation showed practical feasibility with only 30 seconds of communication overhead. Results indicate financial institutions can collaborate to improve model accuracy without sharing sensitive data, enabling better risk management while maintaining compliance and customer trust. This approach provides a viable solution, balancing performance with privacy for enhanced credit risk prediction systems.

My contribution to this research involves the step-by-step implementation and refinement of a decentralized federated learning architecture, making it a practical and accessible tool for various applications. In contrast to many previous studies that often lacked comparative analyses or relied on limited machine learning methods and datasets, this research bridges the gap by providing a more comprehensive and practical approach.This research opens up several significant directions for future work.

In the current implementation, a uniform model architecture was used for all clients in the decentralized federated learning setup. While this approach ensures consistency and simplifies model management, it does not account for the diverse characteristics of each client's data. Future research can explore model diversification, where each client employs a tailored model adapted to its own data distribution and complexity. For instance, clients with significantly different risk profiles, data volumes, or feature distributions may benefit from locally optimized models. Comparing these personalized models to a shared global model may provide valuable insights into the trade-offs between consistency and performance.

Another important direction is communication optimization. The current socket-based architecture introduces noticeable latency and communication overhead, especially as the number of clients grows. To address this, future work could incorporate techniques such as adaptive model compression, quantization, or sparse updates to minimize transmitted data volume. Additionally, exploring asynchronous update strategies and adopting more efficient protocols (e.g., gRPC, MQTT) could further reduce communication delay and improve scalability.

Lastly, deploying the framework in real-world financial environments would offer opportunities to evaluate operational constraints, legal compliance (e.g., with privacy laws), and performance in production settings. These extensions would help mature the decentralized FL approach and accelerate its adoption in sensitive, data-restricted domains such as banking and credit risk management.

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