



Safeguarding Financial Integrity with Interval-Valued Neutrosophic Analytic Hierarchy Process for Sustainable Accounting Systems

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Abstract

Nowadays, financial integrity within sustainable accounting systems is critical endeavor in ensuring intricate landscape of sustainable finance. Detection of financial fraud within sustainable accounting systems is crucial for upholding environmental, social, and governance (ESG) standards and sustaining the integrity of financial practices. Leveraging advanced AI-driven technologies, these systems can effectively analyze abundance of financial data to detect suspicious patterns and anomalies indicative of fraudulent activities. Incorporating Neutrosophic logic into sustainable accounting systems improves the efficiency of financial fraud detection by accommodating inherent uncertainty in complex financial data. By leveraging this ground-breaking technology, organizations can effectively navigate the complex financial landscape while ensuring the integrity of their accounting practices. Neutrosophic logic facilitates the modelling of contradictory and ambiguous information, enabling more nuanced detection and analysis of fraudulent activities that may remain unnoticed. This study develops an automated financial fraud detection using improved sparrow search algorithm with Interval-Valued Neutrosophic Analytic Hierarchy Process (ISSA-IVNAHP) technique. The ISSA-IVNAHP technique aims to protect financial integrity via the identification of financial frauds in Sustainable Accounting Systems. The ISSA-IVNAHP technique incorporates a two-stage process. Initially, the ISSA-IVNAHP method designs ISSA-based feature subset selection approach for the optimal feature selection. Next, in the second stage, the ISSA-IVNAHP technique uses IVNAHP technique for decision-making process that enables to detection of the presence and absence of financial fraud. The simulation results of the ISSA-IVNAHP technique can be examined on financial fraud database. The experimental values reported that the ISSA-IVNAHP methodology attains maximum efficiency over other models

Keywords: Financial Fraud Detection; Sparrow Search Algorithm; Neutrosophic Logic; Sustainable Accounting System; Data Mining

1. Introduction

Financial scam denotes false actions intended to attain an unfair financial benefit, which often results in economic losses for persons, businesses, or financial organizations. Financial fraud has a deep and extensive influence on the administrations tangled in its web [1]. The impacts spread beyond ordinary financial damages, moving upon numerous features that can harshly disturb the constancy and reputation of financial organizations. Businesses are opposed to rising tasks and risk management problems due to severe market competition and the suspicions of the global budget [2]. Given the variations in economies, politics, and business environments in the Asia Pacific area, businesses in Taiwan must endure growing chances in China and Southeast Asia by classifying novel savings and potentials [3]. In the procedure of pursuing steady development and overwhelming problems, companies must fulfil rules and meet global alterations. The business tasks linked with financing in developing markets improve the incentives for handling financial reports to avoid taxes in the home state or to travel capital out of the country [4]. Presently, numerous cases of financial reporting fraud are to upsurge. Every occurrence is a serious shock to stockholders, creditors, and investors, and it costs culture extremely. So, the launch of an effectual method to identify economic reporting fraud is a significant problem [5].

Financial organizations use numerous recognition methods to recognize and moderate fraud hazards. These may contain artificial intelligence (AI), machine learning (ML) algorithms, anomaly recognition, and behavior analysis. Data mining (DM) was used in numerous features of financial study [6]. The DM methods have previously been employed in some fields such as credit card approval, bankruptcy prediction, money-laundering recognition, loan decision, stock analysis, etc. However, study associated with the usage of DM for recognition of economic report fraud is restricted. The research paper aims to forecast the event of financial report fraud in businesses as precisely as possible utilizing intellectual methods. Financial accounting scams can be identified by a human professional by employing his or her practical/judgmental awareness, and delivering he/she has adequate knowledge [7]. But, in this situation, human preference will not be removed and the verdicts incline to be individual. So, we remedy data-driven techniques, which only trust the historical information of fake and well-known businesses and their economic percentages [8]. When DM models (most of them except some numerical ones are AI-based) are utilized to resolve these issues, they function in an effective method by sifting over the reports of fake and well-known businesses. In the procedure, they determine information which is employed to forecast whether an industry will execute financial accounting scam in prospect. Constant observing and real-time sirens are also vital modules [9]. AI is a game-changer in fraud recognition finance, presenting the capability to evaluate vast datasets at speed beyond human ability. ML techniques within the AI structure can adjust and acquire from patterns, allowing more precise recognition of anomalies and rare behaviors [10]. AI models can able to classify complex relations and trends that may go ignored over traditional techniques.

This study develops an automated financial fraud detection using improved sparrow search algorithm with Interval-Valued Neutrosophic Analytic Hierarchy Process (ISSA-IVNAHP) technique. The ISSA-IVNAHP technique aims to protect financial integrity via the identification of financial frauds in Sustainable Accounting Systems. The ISSA-IVNAHP technique incorporates a two-stage process. Initially, the ISSA-IVNAHP technique designs ISSA based feature subset selection approach for optimum feature selections. Next, in the second stage, the ISSA-IVNAHP technique uses IVNAHP technique for decision-making process that enables to detection of the presence and absence of financial fraud. The simulation results of the ISSA-IVNAHP technique can be examined on financial fraud dataset.

2. Related Works

In [11], ML models are developed which may leverage earlier recognized data and effort to expect frauds utilizing data gained from the previous data. This article concentrates on mobile-based money transfers for fraud recognition. This study offers a DL structure for observing and classifying fake actions. Deceptive transactions originated by executing and utilizing an RNN on a fake financial database formed by PaySim. In [12], the Kaggle database was utilized to progress a DL-based model. A new text2IMG conversion method was projected to produce small imageries and then they are served into a convolutional neural networks (CNN) structure with class weight utilizing the reverse frequency model to solve the class inequity problem. ML and DL approaches have been employed to confirm the strong and strength of the projected method. Mienye and Sun [13] offer a strong DL model which contains LSTM and GRU as baseline learners in an ensemble structure, with a multi-layer perceptron (MLP) as the meta-learner.

Sulaiman et al. [14] developed methods that incorporate DL techniques with hyperparameter tuning models. Three DL approaches AutoEncoder (AE), CNN, and LSTM were projected. The experimentations directed on the European credit card fraud database and 3 DL methods establish that the projected techniques attain a trade-off among rate of recognition and accuracy. Fanai and Abbasimehr [15] project a dual-phase structure to identify fake contacts that include a deep AE as a representation learning model, and supervised DL approaches. Specifically, the employed DL methods trained on the converted database which were gained by the deep AE considerably outdo their base classifiers that trained on the original data.

In [16], a new technique has been developed for noticing economic fraud utilizing Quantum Graph Neural Network (QGNN) model. QGNN is a kind of NN, which can procedure graph-structured data and influence of Quantum Computing (QC) technique in order to execute calculations proficiently than traditional NNs. The developed model utilizes Variational QC (VQC) model to enhance the QGNN performance. Maashi et al. [17] concentrate on planning an intellectual credit card fraud recognition and identification method utilizing the Garra Rufa Fish optimizer model with EL (CCFDC-GRFOEL) technique. This approach originates an innovative GRFO-based feature subset selection (GRFO-FSS) method for choosing feature subsets. An EL procedure, including an ELM, Bi-LSTM, and AE were utilized for the fraud contact recognition. Lastly, the pelican optimizer algorithm (POA) is exploited for parameter tuning of the 3 classification algorithms.

3. The Proposed Method

In this study, we have designed automated financial fraud detection using ISSA-IVNAHP technique. The ISSA-IVNAHP technique aims to protect financial integrity via the identification of financial frauds in sustainable accounting systems. The ISSA-IVNAHP technique incorporates a two-stage process. Fig. 1 illustrates the working flow of the ISSA-IVNAHP model.

A. ISSA based Feature Subset Selection

Initially, the ISSA-IVNAHP method develops ISSA-based feature subset selection approach for optimum feature selection. The SSA procedures have the advantages of quick convergence and superior optimizer-searching efficacy [18]. In this part, we briefly present the standard SSO. The standard SSA divides the populace into followers and producers as per every sparrow fitness, and the dual characteristics can substitute during every iteration. During the process of foraging, if any individual sparrow recognizes the occurrence of a hunter, it will rapidly aware and travel. The producers signify 10 to 20 per cent of the complete dimension, and their upgrading instructions for the $t + 1$ th iteration are classified into dual kinds: wide exploration in a secure environment and arbitrary movement in a dangerous situation. R_2 denotes the value of warning, ST signifies the threshold of safety.

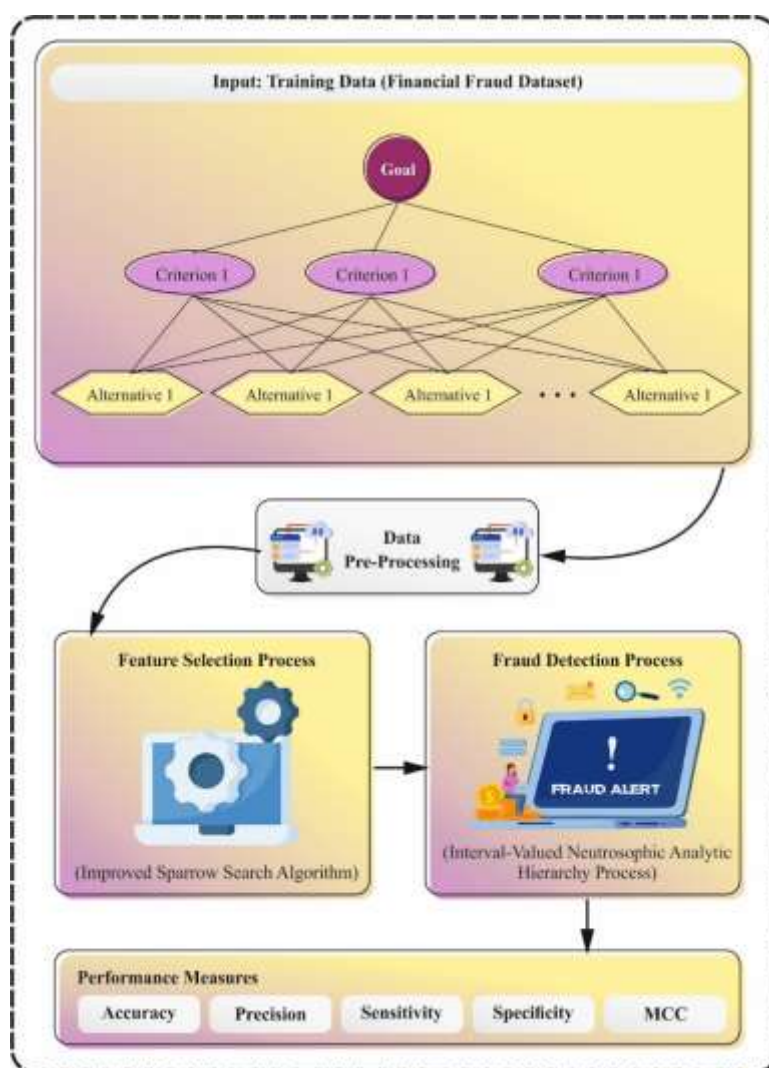


Figure 1: Overall flow of ISSA-IVNAHP technique

Use the 1st line if the value of warning is lesser than threshold; or else, use the 2nd line. The formulation is mentioned below:

$$p_{i,j}^{t+1} = \begin{cases} p_{i,j}^t \cdot \exp\left(-\frac{i}{\alpha \cdot i_{\max}}\right) & \text{if } R_2 < ST \\ p_{i,j}^t + Q \cdot L & \text{if } R_2 \geq ST \end{cases} \quad (1)$$

Here, $t_{\max}$ specifies the highest iterations $\alpha \in (0,1)$; Q fulfils the usual distribution; L is a $1 \times d$ matrix with the complete element of 1. $p_{i,j}$ denotes the producer location of the i^{th} individuals at j^{th} dimension.

The residual sparrows are followers, and the upgraded instruction for the $t + 1^{th}$ iteration was separated into dual kinds such as individuals who search near the position of the optimum producers, and poor fitness value who fly somewhere else to search:

$$F_{i,j}^{t+1} = \begin{cases} Q \cdot \exp\left(\frac{X_{worst} - F_{i,j}^t}{i^2}\right) & \text{if } i > n/2 \\ X_{best}^{t+1} + |F_{i,j}^t - X_{best}^{t+1}| \cdot A^+ \cdot L & \text{otherwise} \end{cases} \quad (2)$$

Whereas, $F_{i,j}$ represents the follower location data; X_{best} refers to the optimum location; X_{worst} is the present place with the worst fitness of global; A refers to the $1 \times d$ matrix with every element arbitrarily considered as positive or negative, and $A^+ = A^T(AA^T)^{-1}$

Supposing that sparrow entities with anti-scrutiny devices signify 1020% of the complete population, whose locations are produced at random, there are dual dissimilar affecting guidelines for every iteration. The formulation is defined as below:

$$S_{i,j}^{t+1} = \begin{cases} X_{best}^t + \beta \cdot |S_{i,j}^t - X_{best}^t| & \text{if } f_i > f_g \\ S_{i,j}^t + K \cdot \left(\frac{S_{i,j}^t - X_{worst}^t}{(f_i - f_w) + \varepsilon}\right) & \text{if } f_i = f_g \end{cases} \quad (3)$$

Here: f_g , f_w and f_i denotes the best, and worst fitness values and existing sparrow individual, correspondingly, β refers to the control parameter that follows the $N(0 \text{ and } 1)$ distribution; $S_{i,j}$ signifies the sentry location data; K represents the sparrow's affecting way and the least constant ε must be inserted to evade being 0.

But the SSA is given to local optimal and slow converge. The abovementioned issues are resolved by using an improved sine chaotic map technique for the early group of sparrow population, presenting the ABC technique to upgrade the locations of producers, and executing mutation optimizer searching.

The chaotic mapping employs chaotic map instructions to plan the optimizer variables to construct higher-quality outcomes than the randomly generated number. Sine and Logistic mapping were generally utilized chaotic mapping models, whereas, it shows that sine chaos displays more clear chaotic assets when equated to the logistic chaos. Therefore, Sine chaotic mapping comes with an easy structure and higher efficacy, but the rough probability density distribution is a main disadvantage. it has been selected to yield a superior early population for SSA. The enhanced sine chaotic formulation is given below:

$$\begin{cases} a_{i+1} = \sin(k\pi a_i) \\ b_{i+1} = \sin(k\pi b_i) \\ y_{i+1} = \{a_{i+1} + b_{i+1}\} \end{cases} \quad (4)$$

Whereas, a_i and b_i takes the interval of $(0 \text{ and } 1)$; k represents the parameter of control; y_{i+1} denotes the repetitive chaotic series value; $\{a_{i+1} + b_{i+1}\}$ indicates the small part of $a_{i+1} + b_{i+1}$. The chaotic system distribution is more even when the controlling parameter is an actual number which is greater than 1000, therefore it has been fixed to 1200. Fig. 2 defines the steps involved in ISSA.

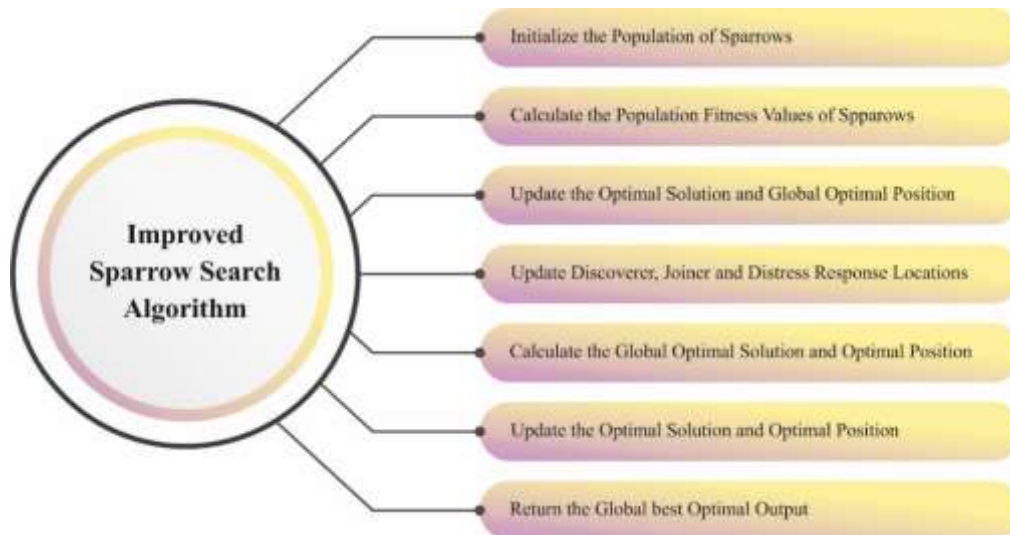


Figure 2: Steps involved in ISSA

In ISSA approach, the function is integrated as a single main formula so that a present weighted identifies all the objective impact [19]. Now, we adopt an FF that combines the objectives of FS:

$$Fitness(X) = \alpha \cdot E(X) + \beta * \left(1 - \frac{|R|}{|N|}\right) \quad (5)$$

Where $Fitness(X)$ indicates the fitness value of X subset, $E(X)$ signifies the classifier error value through the feature selected in the X subset, the amount of attributes chosen and the amount of original attributes in the dataset are $|R|$ and $|N|$ correspondingly, α and β shows the weights of the classifier error and the reduction ratio, $\alpha \in [0,1]$ and $\beta = (1 - \alpha)$.

B. IVNAHP based Decision Making Process

In the second stage, the ISSA-IVNAHP technique uses IVNAHP technique for decision-making process that enables to detection of the presence and absence of financial fraud. Dissimilar techniques were presented to contract with insecurity as the fuzzy model [20]. Atanassov offers intuitionistic fuzzy sets that simplify fuzzy sets which reflect the association of falseness and truth. Smarandache presented neutrosophic logic in order to hold uncertainty well. Uncertainty is very essential in human verdict, which is combined into the recently presented 'Neutrosophic Logic'.

Neutrosophic set (NS) is assumed that each neutrosophy that is a "powerful common formal structure" [21]. It studies the "origin, nature, and scope of neutralities, and their connections with various ideational spectra". NS utilizes uncertainty as a separate assess of membership and nonmembership data. So, the model of NS was assumed that generalized of FS , IFS , and interval-valued sets.

Definition2. Assume U be a universal set and $u \in U$. A NS A in U is defined by truth, uncertainty, and falsity membership function (MF) that are, correspondingly defined as T_A , I_A , and F_A , and demonstrated by $A = \{u, T_A(u), I_A(u), F_A(u) | u \in U\}$. The functions $T_A(u)$, $I_A(u)$ and $F_A(u)$ are real standard and nonstandard subsets of $]0^-, 1^+[$, for instances, $T_A(u): U \rightarrow]0^-, 1^+[$, $I_A(u): U \rightarrow]0^-, 1^+[$, and $F_A(u): U \rightarrow]0^-, 1^+[$. Any constraints can be executed on the sum of $T_A(u)$, $I_A(u)$ and $F_A(u)$, so $0^- \leq \sup T_A(u) + \sup I_A(u) + \sup F_A(u) \leq 3^+$. For a set $u \in U$, $\{T_A(u), I_A(u), F_A(u)\}$, for instance, in simply, $\{T_A, I_A, F_A\}$ is named as neutrosophic number.

Definition3. Complement of NS A is referred by A^c and expressed as $T_A^c(u) = \{1^+\} - T_A(u)$, $I_A^c(u) = \{1^+\} - I_A(u)$, and $F_A^c(u) = \{1^+\} - F_A(u)$, whereas $u \in U$.

Definition4. NS M is stated that compirsed in another NS N , i.e., $M \subseteq N$, if and only if $\inf T_M(u) \leq \inf T_N(u)$, $\sup T_M(u) \leq \sup T_N(u)$, $\inf I_M(u) \geq \inf I_N(u)$, $\sup I_M(u) \geq \sup I_N(u)$, $\inf F_M(u) \geq \inf F_N(u)$, and $\sup F_M(u) \geq \sup F_N(u)$, $\forall u \in U$. At this point, $\inf$ and $\sup$ are utilized to each represents the infimum and supremum functions.

In single valued neutrosophic set (SVNS), the neutrosophic parts are determined under the nearby range of zero and one rather than the non-standard range $]0^-, 1^+[$, to execute them in real life paradigms.

Definition5. Assume U be space of points (objects), with generic element in U implied by u . A SVN A in U is defined by truth, indeterminacy, and falsity MF are demonstrated as T_A , I_A and F_A . For every $u \in U$, $T_A(u)$, $I_A(u)$, $F_A(u) \in [0,1]$. So, a SVN A is illustrated as $A = \{ \{u, T_A(u_i), I_A(u_i), F_A(u_i)\} | u \in U \}$, whereas $0 \leq T_A(u) + I_A(u) + F_A(u) \leq 3$.

Some group of functions among 2 SVN C and D under the universal set V ,

- (1) $C \subseteq D$ if and only if $T_C(v) \leq T_D(v)$, $I_C(v) \geq I_D(v)$, $F_C(v) \geq F_D(v)$, for any $v \in V$.
- (2) $C = D$ if and only if $C \subseteq D$ and $D \subseteq C$.
- (3) Complement of a SVN D is determined as $D^c = \{ \langle v, F_D(v), 1 - I_D(v), T_D(v) \rangle | v \in V \}$.
- (4) $C \cup D = \max(T_C(v), T_D(v)), \min(I_C(v), I_D(v)), \min(F_C(v), F_D(v))$ for any $v \in V$.
- (5) $C \cap D = \min(T_C(v), T_D(v)), \max(I_C(v), I_D(v)), \max(F_C(v), F_D(v))$ for any $v \in V$.
- (6) $C + D = T_C(v) + T_D(v) - T_C(v)T_D(v)$, $I_C(v) + I_D(v) - I_C(v)I_D(v)$, $F_C(v) + F_D(v) - F_C(v)F_D(v)$ for any $v \in V$.
- (7) $C \cdot D = T_C(v)T_D(v)$, $I_C(v)I_D(v)$, $F_C(v)F_D(v)$

The remaining part provides common information regarding neutrosophic sets as well as interval-valued numbers of neutrosophic. In the subsequent calculations, $\tilde{A}$ signifies a set of neutrosophic that are definite in E and denoted by a falsity MF F , truth-MF T and an indeterminacy-MF I .

Definition1. Assume that E as a universe. A SVN $\tilde{A}$ in E has been considered a F_A , I_A and T_A .

$T_A(z)$, $I_A(z)$ and $F_A(z)$ represents the real standard origins of $]^{-}0,1[^{+}$. A NS $\tilde{A}$ is intended by Eq. (6):

$$\tilde{A} = \{ \langle z, (T_A(z), I_A(z), F_A(z)) \rangle : z \in E, (T_A(z), I_A(z), F_A(z)) \in]^{-}0,1[^{+} \} \quad (6)$$

There are no bounds on the sum of $T_A(z)$, $I_A(z)$, and $F_A(z)$, hence $0^{-} \leq T_A(z) + I_A(z) + F_A(z) \leq 3^{+}$.

Definition2. An interval-valued set of neutrosophic $\tilde{N}$ in E considered as $I_N(z)$, $F_N(z)$ and $T_N(z)$, which are stated in Eqs. (7), (8), and (9).

$$T_N(z) = [T_N^L(z), T_N^U(z)] \subseteq [0,1] \quad (7)$$

$$I_N(z) = [I_N^L(z), I_N^U(z)] \subseteq [0,1] \quad (8)$$

$$F_N(z) = [F_N^L(z), F_N^U(z)] \subseteq [0,1] \quad (9)$$

Therefore $\tilde{N}$ is exhibited under Eqs. (10) and (11):

$$\tilde{N} = \{ \langle z, [T_N^L(z), T_N^U(z)], [I_N^L(z), I_N^U(z)], [F_N^L(z), F_N^U(z)] \rangle | z \in E \} \quad (10)$$

$$\tilde{N}^c = \{ \langle z, [F_N^L(z), F_N^U(z)], [1 - I_N^U(z), 1 - I_N^L(z)], [T_N^L(z), T_N^U(z)] \rangle | z \in E \} \quad (11)$$

Whereas, $\tilde{N}^c$ signifies the supplement of $\tilde{N}$

Definition3. For de-eutrophication, an interval-valued number of neutrosophic, Eq. (12), is employed.

$$O(z) = \left(\frac{T_N^L(z) + T_N^U(z)}{2} + (I_N^U(z)) \left(1 - \frac{(I_N^L(z) + I_N^U(z))}{2} \right) - (1 - F_N^U(z)) \left(\frac{F_N^L(z) + F_N^U(z)}{2} \right) \right) \quad (12)$$

Whereas; $\tilde{z}_j = \langle [T_z^L, T_z^U], [I_z^L, I_z^U], [F_z^L, F_z^U] \rangle$

Definition4. The distance of Euclidian computes dual interval-valued numbers of neutrosophic $\tilde{N}_1$ and $\tilde{N}_2$.

The research signifies a complete analysis of the theoretic background of neutrosophic set.

The AHP technique utilizes contrast amongst standards and measures output as the weight of every condition. While AHP was often utilized model in MCDM issues, it has disadvantages. New models combining AHP with Fuzzy Logic have been projected to overwhelm the complexity.

4. Result Analysis

This section illustrates the financial fraud detection results of the ISSA-IVNAHP technique [22]. The dataset comprises 900 samples with two classes as exemplified in Table 1.

Table 1: Details on database

Classes	No. of Samples
Non-Fraud (NFD)	450
Fraud (FD)	450
Total Samples	900

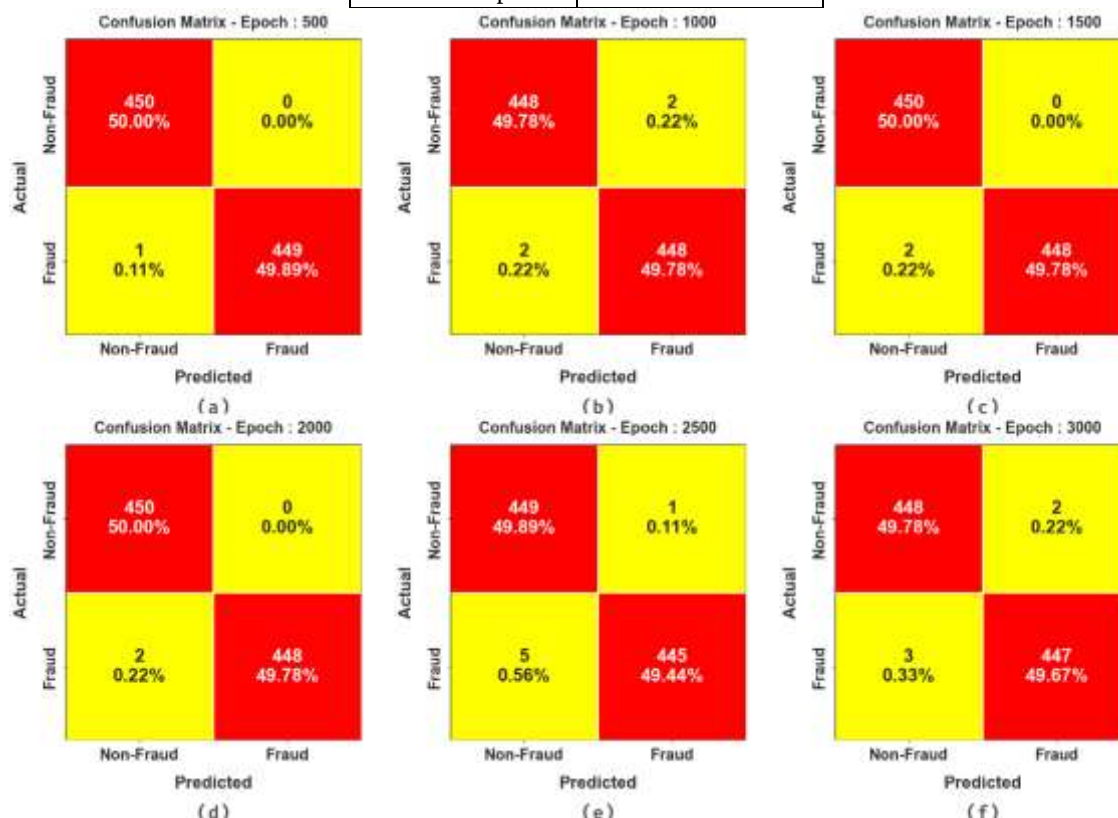


Figure 3: Confusion matrices of ISSA-IVNAHP technique (a-f) Epochs 500-3000

Fig. 3 demonstrates the confusion matrices produced by the ISSA-IVNAHP method on various epochs. The outcomes specify that the ISSA-IVNAHP method has effectual recognition of the fraud and non-fraud samples under all classes.

Table 2 provides a detailed overall recognition result of the ISSA-IVNAHP method on several epochs. Fig. 4 inspects a comparison analysis of the ISSA-IVNAHP technique in terms of $accu_y$, $prec_n$, and MCC. The figure highlighted that the ISSA-IVNAHP technique properly recognized the samples with $accu_y$, $prec_n$, and MCC of 99.89%, 99.89%, and 99.78%, correspondingly. At the same time, with 1000 epochs, the ISSA-IVNAHP method properly recognized the samples with $accu_y$, $prec_n$, and MCC of 99.56%, 99.56%, and 99.11%, correspondingly. Besides, with 1500 epochs, the ISSA-IVNAHP technique properly recognized the samples with $accu_y$, $prec_n$, and MCC of 99.78%, 99.78%, and 99.56%, correspondingly. At last, with 3000 epochs, the ISSA-IVNAHP technique properly recognized the samples with $accu_y$, $prec_n$, and MCC of 99.44%, 99.44%, and 98.89 %, correspondingly.

Fig. 5 inspects a comparison study of the ISSA-IVNAHP method in terms of $sens_y$ and $spec_y$. The figure highlighted that the ISSA-IVNAHP technique correctly recognized the samples with $sens_y$ and $spec_y$ of 99.89% and 99.89%, correspondingly. Simultaneously, with 1000 epochs, the ISSA-IVNAHP method correctly recognized the samples with $sens_y$ and $spec_y$ of 99.56% and 99.56%, correspondingly. In addition, with 1500 epochs, the ISSA-IVNAHP technique properly detected the samples with $sens_y$ and $spec_y$ of 99.78% and 99.78%, correspondingly. Finally, with 3000 epochs, the ISSA-IVNAHP method properly identified the samples with $sens_y$ and $spec_y$ of 99.44% and 99.44%, correspondingly.

Table 2: Recognition result of the ISSA-IVNAHP technique under several epochs

Classes	$Accu_y$	$Prec_n$	$Sens_y$	$Spec_y$	MCC
Epoch500					
NFD	100.00	99.78	100.00	99.78	99.78
FD	99.78	100.00	99.78	100.00	99.78
Average	99.89	99.89	99.89	99.89	99.78
Epoch1000					
NFD	99.56	99.56	99.56	99.56	99.11
FD	99.56	99.56	99.56	99.56	99.11
Average	99.56	99.56	99.56	99.56	99.11
Epoch1500					
NFD	100.00	99.56	100.00	99.56	99.56
FD	99.56	100.00	99.56	100.00	99.56
Average	99.78	99.78	99.78	99.78	99.56
Epoch2000					
NFD	100.00	99.56	100.00	99.56	99.56
FD	99.56	100.00	99.56	100.00	99.56
Average	99.78	99.78	99.78	99.78	99.56
Epoch2500					
NFD	99.78	98.90	99.78	98.89	98.67
FD	98.89	99.78	98.89	99.78	98.67
Average	99.33	99.34	99.33	99.33	98.67
Epoch3000					
NFD	99.56	99.33	99.56	99.33	98.89
FD	99.33	99.55	99.33	99.56	98.89
Average	99.44	99.44	99.44	99.44	98.89

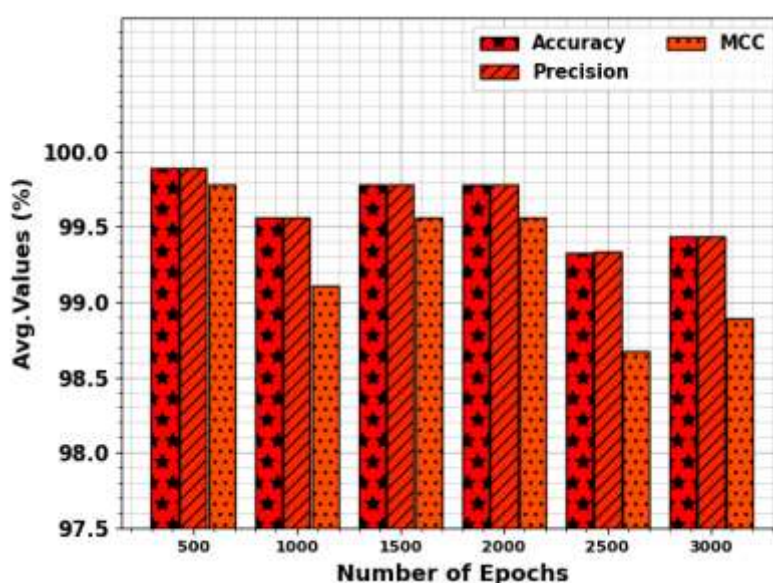


Figure 4: $Accu_y$, $prec_n$, and MCC of the ISSA-IVNAHP technique under several epochs

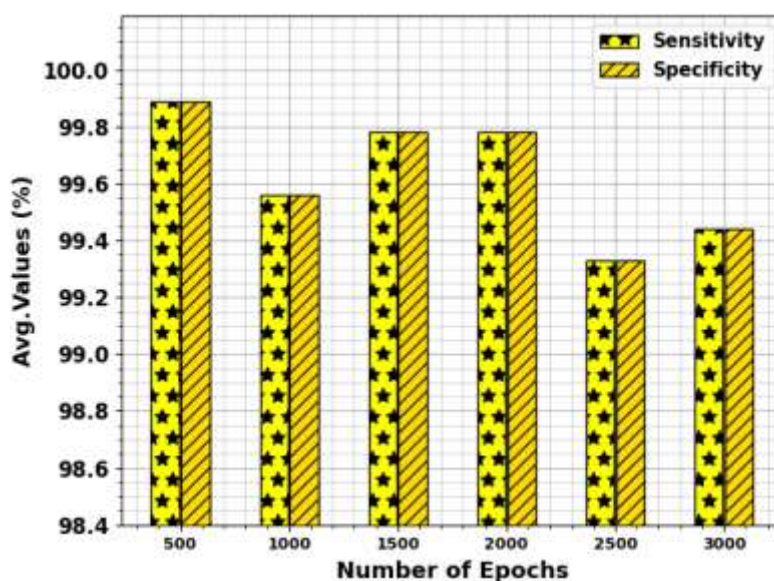


Figure 5: $Sens_y$ and $spec_y$ of the ISSA-IVNAHP technique under several epochs

The performance of the ISSA-IVNAHP outcome is graphically represented in Fig. 6 in the form of training accuracy (TRAA) and validation accuracy (VALA) curves under 500 epochs. The figure displays useful interpretation of the behaviour of the ISSA-IVNAHP model over several epoch counts, illustrating its learning process and generalization abilities. Remarkably, the figure infers a steady improvement in the TRAA and VALA with progress in epochs. It ensures the adaptive nature of the ISSA-IVNAHP technique in the pattern detection method on TR and TS data. The rising trend in VALA outlines the capability of the ISSA-IVNAHP model to adapt to the TR data and also excels in providing accurate classification of hidden data, illustrating robust generalization abilities.

Fig. 7 illustrates a comprehensive representation of the training loss (TRLA) and validation loss (VALL) outcomes of the ISSA-IVNAHP method on 500 epochs. The progressive decline in TRLA highlights the ISSA-IVNAHP model optimizing the weights and minimizing the classifier error on the TR and TS datasets. The figure illustrates a clear understanding of the ISSA-IVNAHP model's association with the TR dataset, which highlights its proficiency in capturing patterns within both datasets. Notably, the ISSA-IVNAHP method continually improves its parameters in decreasing the variances amongst the prediction and real TR class labels.

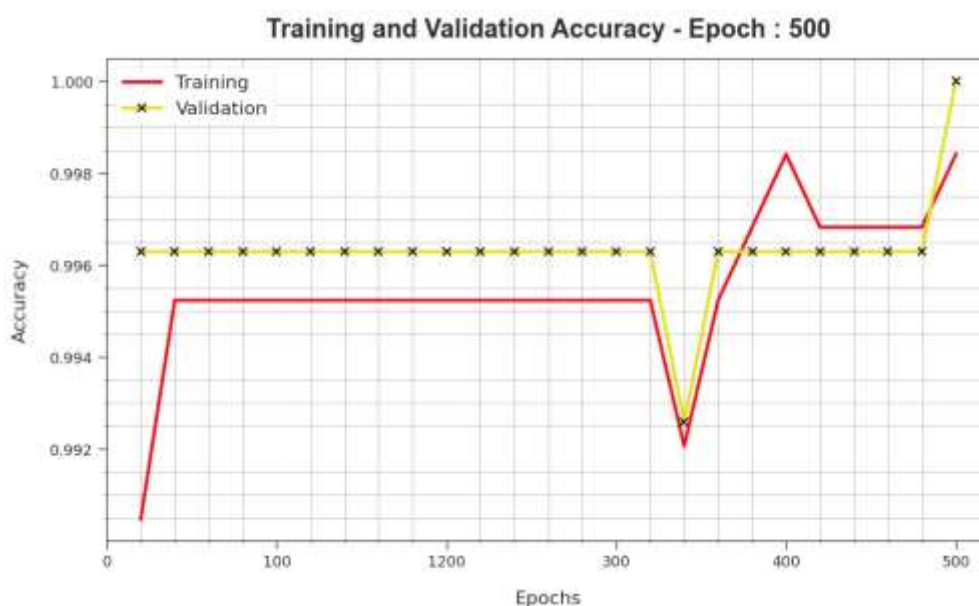


Figure 6: $Accu_y$ curve of the ISSA-IVNAHP technique under 500 epochs

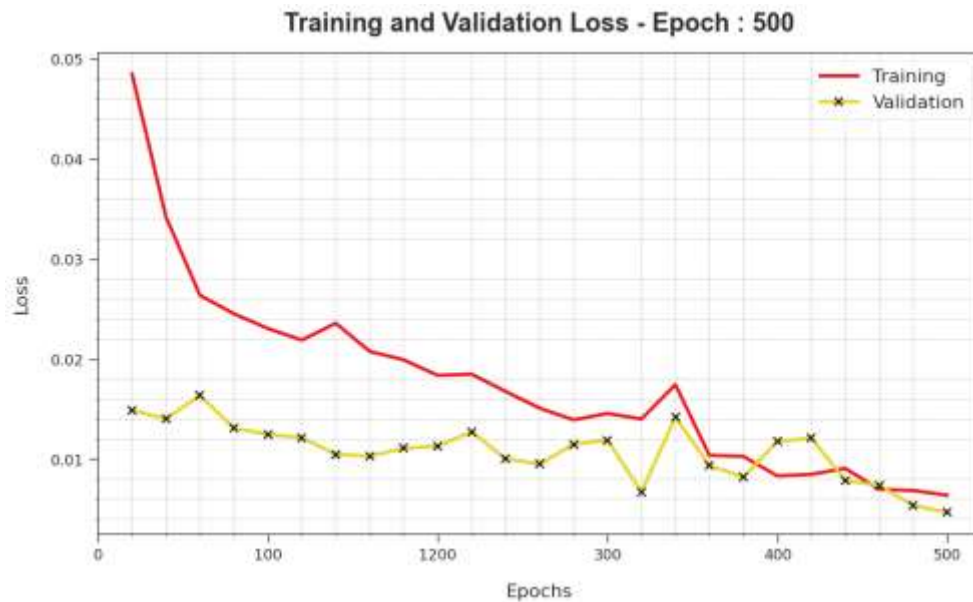


Figure 7: Loss curve of the ISSA-IVNAHP technique under 500 epochs

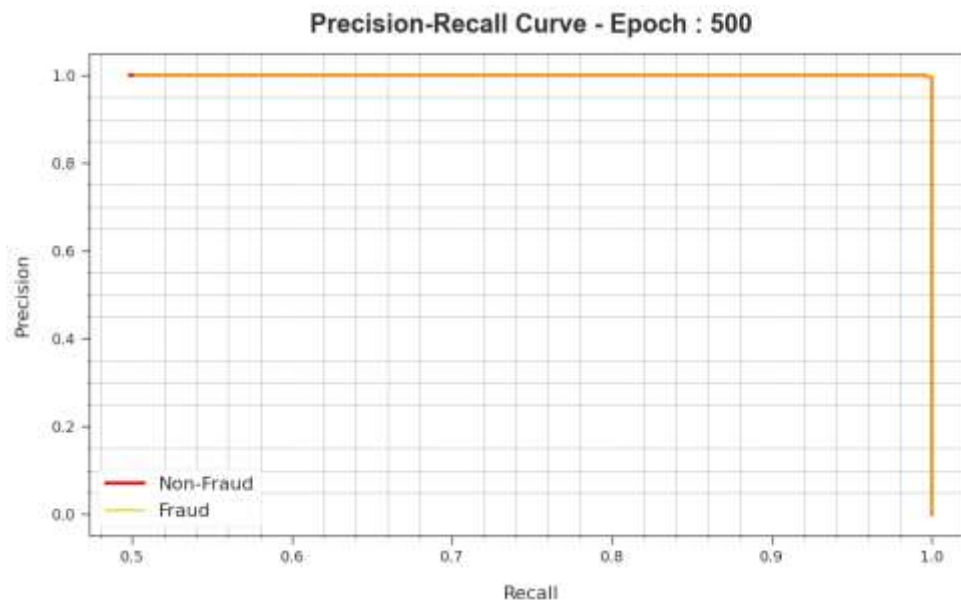


Figure 8: PR curve of the ISSA-IVNAHP technique under 500 epochs

Inspecting the precision recall (PR) curve, as given in Fig. 8, the outcomes ensured that the ISSA-IVNAHP technique progressively obtains better PR values through over each class under 500 epochs. It verifies the enhanced capabilities of the ISSA-IVNAHP technique in the detection of various classes, demonstrating proficiency in the detection of classes.

Furthermore, in Fig. 9, ROC curves generated by the ISSA-IVNAHP technique outperform the classification of various labels under 500 epochs. It provides comprehensive understanding of the tradeoff between TPR and FRP over dissimilar recognition threshold values and epoch counts. The figure underlined the improved classifier outcomes of the ISSA-IVNAHP method under all classes, outlining the effectiveness in addressing numerous classification issues.

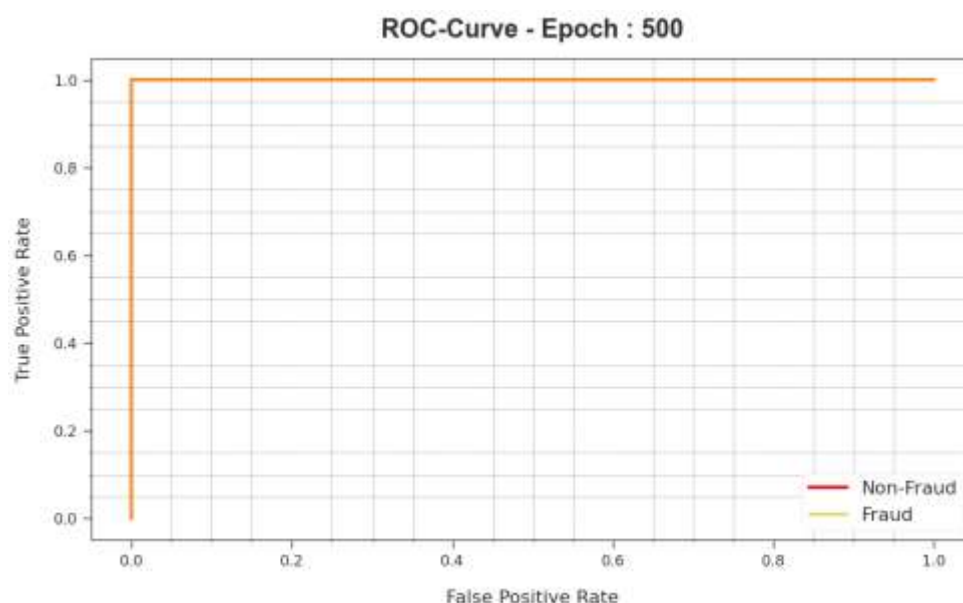


Figure 9: ROC curve of the ISSA-IVNAHP technique under 500 epochs

An overall comparison study of the ISSA-IVNAHP technique is provided in Table 3 and Fig. 10 [17]. Based on $accu_y$, the ISSA-IVNAHP technique offers higher $accu_y$ of 99.89% while the CCFDC-GRFOEL, DSGBT, DTGBT, DTDS, DTDS, RFGBT, DTNB, and OCSODL-CCFD models obtain lower $accu_y$ of 99.58%, 98.28%, 99.01%, 98.93%, 98.95%, 98.32%, and 99.25%, correspondingly. Also, based on MCC, the ISSA-IVNAHP technique offers higher MCC of 99.78% while the CCFDC-GRFOEL, DSGBT, DTGBT, DTDS, DTDS, RFGBT, DTNB, and OCSODL-CCFD techniques attain lower MCC of 99.14%, 98.95%, 98.52%, 98.18%, 98.23%, 98.35%, and 98.81%, correspondingly. Thus, the ISSA-IVNAHP technique can be applied for enhanced fraud detection process.

Table 3: Comparative outcome of IVNAHP methodology with other approaches

Methods	Accuracy	MCC
ISSA-IVNAHP	99.89	99.78
CCFDC-GRFOEL	99.58	99.14
DSGBT Model	98.28	98.95
DTGBT Model	99.01	98.52
DTDS Algorithm	98.93	98.18
RFGBT Algorithm	98.95	98.23
DTNB Algorithm	98.32	98.35
OCSODL-CCFD	99.25	98.81

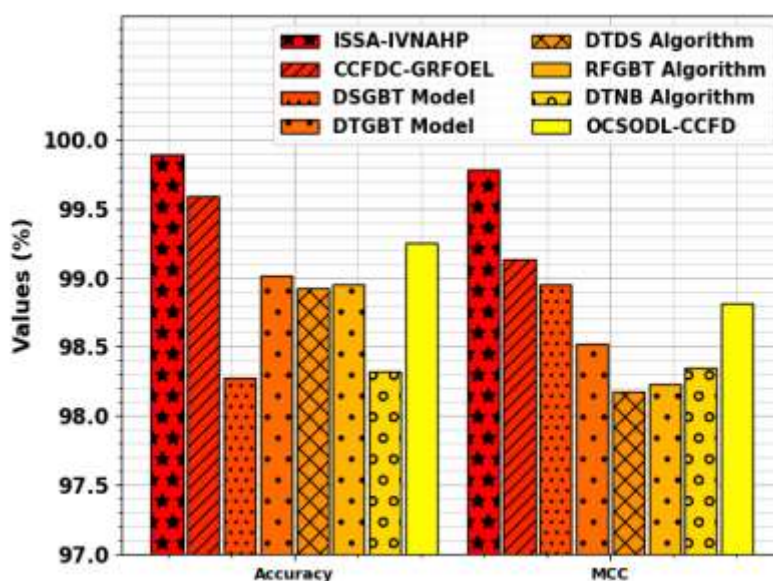


Figure 10: Comparative analysis of IVNAHP technique with other methodologies

5. Conclusion

In this study, we have designed an automated financial fraud detection using ISSA-IVNAHP technique. The ISSA-IVNAHP technique aims to protect financial integrity via the identification of financial frauds in sustainable accounting systems. The ISSA-IVNAHP technique incorporates a two-stage process. Initially, the ISSA-IVNAHP technique designs ISSA-based feature subset selection approach for optimum feature selection. Next, in the second stage, the ISSA-IVNAHP technique uses IVNAHP technique for decision-making process which enables to detection of the presence and absence of financial fraud. The simulation outcomes of the ISSA-IVNAHP technique can be examined on the financial fraud database. The simulation values reported that the ISSA-IVNAHP methodology gains better performance than other systems.

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References

- [1] Poongodi, K.; Kumar, D. Support vector machine with information gain based classification for credit card fraud detection system. *Int. Arab J. Inf. Technol.* 2021, 18, 199–207.
- [2] Benchaji, I.; Douzi, S.; El Ouahidi, B.; Jaafari, J. Enhanced credit card fraud detection based on attention mechanism and LSTM deep model. *J. Big Data* 2021, 8, 1–21.
- [3] Velicheti, S.S.; Pavan, A.S.H.; Reddy, B.T.; Srikala, N.V.; Pranay, R.; Kannaiah, S.K. The Hustlee Credit Card Fraud Detection using Machine Learning. In *Proceedings of the 2023 7th International Conference on Computing Methodologies and Communication (ICCMC)*, Erode, India, 21–23 February 2023; pp. 139–144.
- [4] Strelcenia, E.; Prakoonwit, S. Improving Classification Performance in Credit Card Fraud Detection by Using New Data Augmentation. *AI* 2023, 4, 172–198.
- [5] Han, S.; Zhu, K.; Zhou, M.; Cai, X. Competition-driven multimodal multiobjective optimization and its application to feature selection for credit card fraud detection. *IEEE Trans. Syst. Man Cybern. Syst.* 2022, 52, 7845–7857.
- [6] Zhang, X.; Han, Y.; Xu, W.; Wang, Q. HOBA: A novel feature engineering methodology for credit card fraud detection with a deep learning architecture. *Inf. Sci.* 2021, 557, 302–316.
- [7] Mustaqim, A.Z.; Adi, S.; Pristyanto, Y.; Astuti, Y. The effect of recursive feature elimination with cross-validation (RFECV) feature selection algorithm toward classifier performance on credit card fraud detection. In *Proceedings of the 2021 International Conference on Artificial Intelligence and Computer Science Technology (ICAICST)*, Yogyakarta, Indonesia, 29–30 June 2021; pp. 270–275.
- [8] Malik, E.F.; Khaw, K.W.; Belaton, B.; Wong, W.P.; Chew, X. Credit card fraud detection using a new hybrid machine learning architecture. *Mathematics* 2022, 10, 1480.

- [9] Prabhakaran, N.; Nedunchelian, R. Oppositional Cat Swarm Optimization-Based Feature Selection Approach for Credit Card Fraud Detection. *Comput. Intell. Neurosci.* 2023, 2023, 2693022.
- [10] Chang, V.; Di Stefano, A.; Sun, Z.; Fortino, G. Digital payment fraud detection methods in digital ages and Industry 4.0. *Comput. Electr. Eng.* 2022, 100, 107734.
- [11] Nama, F.A. and Obaid, A.J., 2024. Financial Fraud Identification Using Deep Learning Techniques. *Al-Salam Journal for Engineering and Technology*, 3(1), pp.141-147.
- [12] Alharbi, A., Alshammari, M., Okon, O.D., Alabrah, A., Rauf, H.T., Alyami, H. and Meraj, T., 2022. A novel text2IMG mechanism of credit card fraud detection: A deep learning approach. *Electronics*, 11(5), p.756.
- [13] Mienye, I.D. and Sun, Y., 2023. A deep learning ensemble with data resampling for credit card fraud detection. *IEEE Access*, 11, pp.30628-30638.
- [14] Sulaiman, S.S., Nadher, I. and Hameed, S.M., 2024. Credit Card Fraud Detection Using Improved Deep Learning Models. *Computers, Materials & Continua*, 78(1).
- [15] Fanai, H. and Abbasimehr, H., 2023. A novel combined approach based on deep Autoencoder and deep classifiers for credit card fraud detection. *Expert Systems with Applications*, 217, p.119562.
- [16] Innan, N., Sawaika, A., Dhor, A., Dutta, S., Thota, S., Gokal, H., Patel, N., Khan, M.A.Z., Theodonis, I. and Bennai, M., 2024. Financial fraud detection using quantum graph neural networks. *Quantum Machine Intelligence*, 6(1), pp.1-18.
- [17] Maashi, M., Alabduallah, B. and Kouki, F., 2023. Sustainable financial fraud detection using garra rufa fish optimization algorithm with ensemble deep learning. *Sustainability*, 15(18), p.13301.
- [18] Chen, Y., Li, X. and Zhao, S., 2024. A Novel Photovoltaic Power Prediction Method Based on a Long Short-Term Memory Network Optimized by an Improved Sparrow Search Algorithm. *Electronics*, 13(5), p.993.
- [19] Mafarja, M., Thaher, T., Al-Betar, M.A., Too, J., Awadallah, M.A., Abu Doush, I. and Turabieh, H., 2023. Classification framework for faulty-software using enhanced exploratory whale optimizer-based feature selection scheme and random forest ensemble learning. *Applied Intelligence*, pp.1-43.
- [20] Yiğit, F., 2023. A three-stage fuzzy neutrosophic decision support system for human resources decisions in organizations. *Decision Analytics Journal*, 7, p.100259.
- [21] Das, S., Roy, B.K., Kar, M.B., Kar, S. and Pamučar, D., 2020. Neutrosophic fuzzy set and its application in decision making. *Journal of Ambient Intelligence and Humanized Computing*, 11, pp.5017-5029.
- [22] <https://www.kaggle.com/datasets/mlg-ulb/creditcardfraud>