An Enhanced Risk Prediction Framework for Blockchain-based Financial Transactions Using Interval Neutrosophic Covering Rough Sets with Heuristic Search

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Abstract

The most efficient device for modelling uncertainty in decision-making issues is the neutrosophic set (NS) and its add-ons, such as NS of complex, interval, and interval complex. An efficient device for establishing uncertainty in decision-making by inserting three grades of truth, indeterminacy, and falsehood of an established statement. Recently, financial globalization has significantly expanded various methods for enhancing service quality using advanced resources. The practical application of the blockchain (BC) model enables stakeholders concerned about the hazard and return prediction models of economic products. To explore the application of deep learning (DL) in processing financial trading data, a neural network (NN) and DL data are utilized. Absolute stock indices and financial data are utilized for analyzing the efficiency of these models in financial prediction and analysis. This paper presents an Enhanced Risk Prediction Framework for Financial Transactions System Using Interval Neutrosophic Covering Rough Sets (ERPFFTS-INCRS) model. The aim is to develop an effective risk prediction model that enhances the reliability and security of BC financial transactions under uncertain conditions, utilizing neutrosophic logic. Initially, the z-score standardization method is used to clean, transform, and organize raw data into a structured and meaningful format. Furthermore, the ERPFFTS-INCRS method implements the INCRS method for the financial classification process. Finally, the hyperparameter selection for the INCRS model is performed by implementing the Elephant Herding Optimisation (EHO) algorithm. The experimental evaluation of the ERPFFTS-INCRS approach is examined under the metaverse financial transactions (MFT) dataset. The comparison analysis of the ERPFFTS-INCRS approach revealed a superior accuracy value of 98.77% compared to existing methods.

DOI: https://doi.org/10.54216/IJNS.270111

Keywords: Risk Prediction Framework; Blockchain; Financial Transactions; Neutrosophic Set; Fuzzy Set; Interval Neutrosophic Covering Rough Sets

1. Introduction

Neutrosophic Logic is an emerging area of research that evaluates each statement based on three components: the degree of truth represented by a subset T, the degree of indeterminacy represented by a subset I, and the degree of falsity represented by a subset F [1]. The NS is effectively employed for processing indeterminate data, offering significant advantages in managing the uncertainty inherent in information. It is widely recommended for data analysis and classification tasks [2]. With the rise of computer technologies, innovation-led and technology-focused approaches have become a key driver of global economic development [3]. According to the national congress statement, India's economy is transitioning from a phase of rapid growth to one of high-standard advancement. As a crucial pillar of China's national economy, the sustained growth of small and medium enterprises (SMEs) serves as the foundation for continuing steady national economic development. Still, SMEs encounter challenges, such as limited and costly access to financing, which obstruct their growth [4]. Within the framework of the Internet, financial transactions in the supply chain serve as an efficient method for financial reform and economic expansion. As one of the recent evolving techniques, BC holds a promising outlook. BC is a large-scale collaboration tool applicable to all types of registration, transactions, and inventory management. The financial market operates on a broad level, allowing for multi-party interaction and supporting transactions at moderate frequencies [5]. The inclusion of BC technologies in financial transactions holds notable theoretical and real-world importance. Extracting insights from financial transaction information and predicting transaction patterns remains a prominent area of research [6]. Fig. 1 represents the general structure of financial transactions using BC technology.

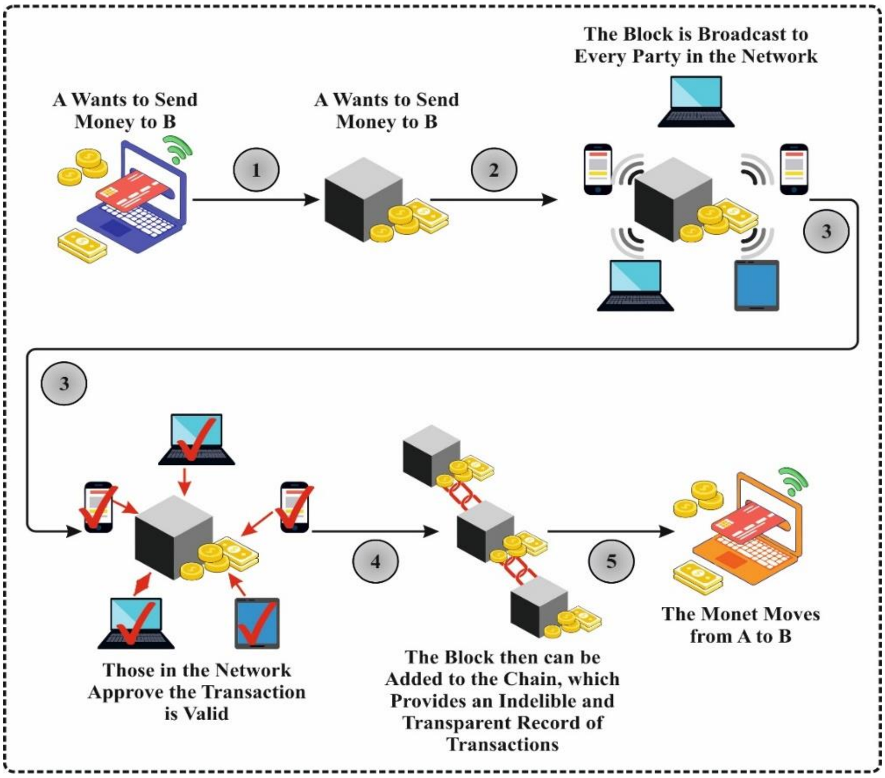

Figure 1. BC-based financial transactions system

The progression of artificial intelligence (AI) has undergone significant changes over the years, introducing numerous efficient applications that contribute to a more convenient modern lifestyle [7]. One notable investigative area of AI methods is machine learning (ML), which utilizes labelled or unlabeled input data to determine proper rules for identifying known data or forecasting future outcomes [8]. Presently, the global economy is experiencing rapid growth, and with it, various barriers limiting industrial development are being addressed through the rapid rise of resources [9]. The structure of socio-economic improvement defines these markets. It regulates or governs the allocation of the entire economic and social framework and thus becomes a vital component of socio-economic progress. Furthermore, AI and BC tools have evolved as transformative forces in the financial domain, significantly reducing credit-related risks [10].

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- The ERPFFTS-INCRS model applies Z-score standardization to pre-process raw financial data by normalizing features to have zero mean and unit variance. The model mitigates variability and enhances dataset consistency. This transformation enables more effective feature representation, improving the performance and reliability of the classification model.
- The ERPFFTS-INCRS method employs the INCRS technique to develop a financial classification model, effectively managing uncertainty and imprecision in intrinsic data. This approach captures truth, indeterminacy, and falsity membership intervals, enabling more accurate classification of ambiguous financial transactions and improving decision-making under uncertain conditions.
- The performance of the ERPFFTS-INCRS technique was enhanced by integrating the EHO model to optimize the hyperparameters of the INCRS model. This adaptive optimization technique efficiently searches the parameter space, enhancing classification accuracy and convergence speed, which results in a more robust and reliable financial classification system.
- The novelty of the ERPFFTS-INCRS methodology lies in its integration of neutrosophic theory with advanced optimization techniques for hyperparameter tuning, thereby addressing uncertainty and imprecision in financial data more effectively than conventional methods. This incorporation enables more precise modelling of ambiguous data and adaptive optimization, leading to improved classification accuracy. It presents a robust solution constructed for complex and uncertain financial environments, thus outperforming existing models.

2. Related Works

Biswas et al. [11] proposed a new DL approach, which merges a TCN alongside an Attention mechanism (AM) for predicting stock prices. Zhou et al. [12] proposed a trading strategy optimizer technique depending on TCN. TCN enhances the modelling capability of market dynamics through dilated and causal convolution mechanisms, while also enabling effective parallel computing abilities. Experimental outcomes demonstrate that this technique is more advanced than conventional approaches in terms of risk control, cumulative yield, and prediction accuracy, and significantly enhances the stability of trading approaches. Xiao et al. [13] presented a new methodology for detecting anomalous payment behaviours and predicting financial threats in SMEs, utilizing an optimized LSTM-AM. This methodology incorporates bi-directional LSTM networks alongside a multi-head AM for capturing intricate temporal relations in payment forms, though concentrating on important transaction features. The methodology addresses the challenges of emerging payment patterns through a detailed risk assessment approach and a dynamic threshold adjustment mechanism.

Ilori et al. [14] presented a system for incorporating sophisticated data analytics into the internal audit process, aiming to deliver stronger risk management and improved fraud detection capabilities. Incorporate various data sources, including operational, financial, and external data, to provide a comprehensive understanding of the organization's risk landscape. Employ ML models and predictive analytics for pattern identification, future risk prediction, and anomaly detection. Bai et al. [15] explored the use of generative AI in financial market data management and prediction. By combining numerous data sources and feature extractor methods, namely technical indicators, fundamental analysis, sentiment analysis, and global economic data, generative AI creates a detailed DL model, which highly improves financial data management effectiveness and market predictions' accuracy.

Gu [16] introduced a BP-based NN to design an Optimum Risk Prediction (ORP-BNN) model for prevalidating current and novel financial imbalances. This model is designed to facilitate business protocols and ensure risk-free financial management. Li et al. [17] proposed an approach to predict credit risk for listed companies using a CNN-LSTM and a neural network (NN). This technique relies on the assistance of the LSTM network for predicting long-range time sequences, combined with the CNN technique. Additionally, the advantages of incorporating a CNN and LSTM paradigm include reducing data complexity, enhancing the model's training and calculation speed, and addressing the limitation of past data in the long-range LSTM approach's sequence prediction.

3. The Proposed Methodology

In this paper, an ERPFFTS-INCRS technique is proposed. The aim is to develop an effective risk prediction model that enhances the reliability and security of BC financial transactions under uncertain conditions, utilizing neutrosophic logic. Fig. 2 represents the workflow of the ERPFFTS-INCRS model.

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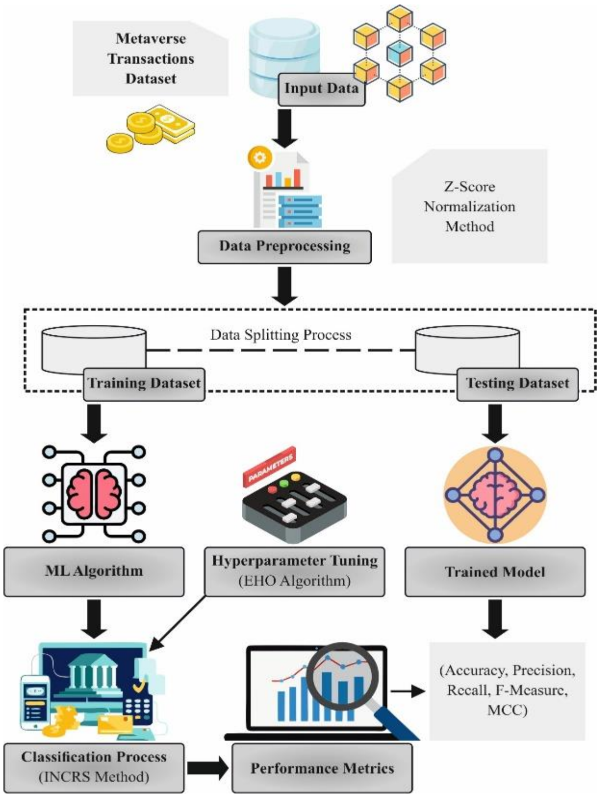

Figure 2. Workflow of ERPFFTS-INCRS approach

A. Z-score Normalization

Initially, the z-score normalization method is employed in the data pre-processing step [18]. This method is chosen for its capability to standardize data by converting features to have a mean of zero and a standard deviation of one, which effectively mitigates bias caused by varying scales in the raw data. Z-score normalization maintains the original data distribution while handling extreme values more robustly, unlike min-max scaling, which compresses data into a fixed range and can be sensitive to outliers. This makes the model most appropriate for financial datasets, where the presence of outliers and varying feature ranges is familiar. The model also enhances the convergence speed and stability of various ML models by ensuring consistent feature scales, ultimately improving the performance and reliability of the model compared to other normalization methods.

As part of pre-processing, data normalization comprises scaling features to hold a standard distribution that is vital for the pre-processing stage in ML. Various ML models are sensitive to scale data, particularly those that employ distance metrics. Every feature contributes equally to the distance calculation utilizing normalization. Furthermore, in the gradient descent optimizer that is used to train NNs, normalized data allows for faster convergence. Normalization restricts features with wider ranges from controlling the process of learning. In this study, Z-score normalization is utilized to normalize the data. This method modifies the data to have a mean of zero and a standard deviation (SD) of one. The x_i, normalizing the value of x_i for the parameter X, is calculated:

$$x_i = \frac{x_i - \mu}{\sigma} \tag{1}$$

Here, σ and μ refer to the SD and mean of parameter X, respectively.

B. INCRS-based Classification Process

Followed by, the ERPFFTS-INCRS model implements the INCRS method for the financial classification process, particularly in uncertain and imprecise FinTech environments [19]. This model is chosen for its ability to handle uncertainty, imprecision, and incomplete data, which are prevalent in financial data. Unlike conventional rough sets or fuzzy sets, interval neutrosophic sets capture three membership degrees — truth, indeterminacy, and falsity — providing a more comprehensive representation of ambiguity. This enables the model to discriminate subtle variances in complex transaction data better, thereby enhancing classification accuracy. Moreover, INCRS integrates neutrosophic logic with covering rough sets, enabling flexible approximations that adapt to varying data granularities. Compared to conventional classifiers, INCRS offers enhanced robustness in uncertain environments, making it particularly suitable for dynamic and noisy financial applications.

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This approach is based on neutrosophic theory, which extends classical logic by introducing degrees of truth, indeterminacy, and falsity, making it highly appropriate for modelling incomplete or inconsistent financial data. By integrating Interval Neutrosophic Sets (INS) with covering rough set theory, the model shows efficiency in capturing the uncertainty and vagueness inherent in real-world financial datasets, improving decision-making accuracy. INS are an extension of neutrosophic sets designed to handle uncertain, imprecise, and inconsistent data. For a given universe X, an INS A assigns to each element $x \in X$ three membership intervals: a truth-membership $T_A(x)$, an indeterminacy-membership $I_A(x)$, and a falsity-membership $F_A(x)$, all in the range [0,1]. These intervals are illustrated as $T_A(\mathrm{x}) = [T_A^L(x), T_A^U(x)], I_A(x) = [I_A^L(x), I_A^U(x)], F_A(x) = [F_A^L(x), F_A^U(x)]$. The complement of an INS reverses the roles of truth and falsity while adjusting indeterminacy. The membership intervals are utilized for evaluating similarity or dominance when comparing two INSs. This structure enables INSs to capture uncertainty in decision-making processes, such as financial risk classification.

The neutrosophic covering rough sets process addresses indeterminacy in transactions by defining lower and upper approximations of a set $A \subseteq X$, which represent the elements that certainly and possibly belong to A, respectively. Formally, the lower approximation $\underline{N}(A)$ comprises all elements whose neutrosophic membership intervals fully satisfy the criteria of A, while the upper approximation $\overline{N}$ consists of elements whose membership intervals partially meet these criteria. These approximations integrate truth, indeterminacy, and falsity membership functions, enabling precise handling of ambiguous or incomplete transaction data.

Definition_2.1: Accept X to be the space of facts by a class of components represented by x. During X, the $NS\ A$ was abridged using an indeterminacy-membership function (IMF) $I_{A(x)}$, a truth-MF (TMF) $T_{A(x)}$, and a falsity-MF (FMF) $F_{A(x)}$.

Definition_2.2: Suppose X acts as a space of objects using the form of components in X represented by x. A single-valued NS N in X was condensed using an IMF $I_{N(x)}$, FMF $F_{N(x)}$, and TMF $T_{N(x)}$. Following, an INS A is characterized as shown:

$$A = \{\langle x, T_A(x), I_A(x), F_A(x)\rangle | x \in X\} \tag{2}$$

Definition_2: The counterpart of the INS $A = \langle T_A, l_A, F_A\rangle = \{[T_A^L, T_A^U], [I_A^L, I_A^U], [F_A^L, F_A^U]\}$ is represented by A^c and that was named as $A^c = \{[F_A^L, F_A^U]_t [1 - I_A^U, 1 - I_A^L], [T_A^L, T_A^U$.

Definition_2.4: $A = \{\langle x, T_A(x), I_A(x) F_A(x)\rangle\}$ and $B = \{\langle x, T_B(x), I_B(x) F_B(x)\rangle\}$ are two INS, however $T_A(\mathrm{x}) = [T_A^L(x), T_A^U(x)], I_A(x) = [I_A^L(x), I_A^U(x)], F_A(x) = [F_A^L(x), F_A^U(x)]$, and $T_B(x) = [T_B^L(x), T_B^U(x)], l_B(x) = [I_B^L(x), I_B^U(x)], F_B(x) = [F_B^L(x), F_B^U(x)]$.

Definition_2.5: A and B are 2 INNs, having noted below the fundamental tools of INNs.

The INCRS approach extends conventional rough set theory by integrating interval neutrosophic sets to handle uncertainty and imprecision in data effectively. This method can be applied in various decision-making scenarios to manage ambiguous data. It also defines a cover of the universe X as a family of interval neutrosophic subsets, each characterized by truth, indeterminacy, and falsity intervals in $the\ interval$ $[s, t]$. These covers approximate objects in X by grouping elements with similar neutrosophic properties, enabling refined analysis of incomplete or uncertain data. Moreover, when the intervals collapse to a single value β, the cover is called an IN β cover, representing a more specific classification region. This framework also allows defining smaller components and their corresponding signs within the INCRS structure.

Definition_3.1: Suppose X is a space of objects. For some $[\mathrm{s}, t] \in [0,1]$ and $= \{C_1, C_2, \dots, C_m\}$, whereas $C_i = \{T_{c,i} l_{c_i}, F_{c_i}\}$ and $C_i \in lNS(i = 1_t 2_\leq \dots, m)$.

Definition_3.2: Presume $C = \{C_1, C_2, \dots, C_m\}$ be IN $[\mathrm{s}, t]$ protect of X. If $0 \leq [s', t'] \leq [\mathrm{s}, t], C$ symbolizes an IN $[s', t']$ covers of X.

Definition_3.3: Let $C = \{C_1, C_2, \dots, C_m\}$ symbolizes IN $[\mathrm{s}, t]$ protect of X. If $s = t = \beta$, then C is named an IN β covers of X.

Definition_3.4: Suppose $C = \{C_1, C_2, \dots, C_m\}$ be IN $[\mathrm{s}, t]$ covers of$X$, while $C_i = \{\mathrm{T_{c,i}}, \mathrm{I_{c_i}}, F_{c_i}\}$ and $C_i \in lNS(i = 1,2, \dots, m)$. For $\forall x \in X$, the IN $[s, t]$ area of x.

Definition_3.5: Assume $C = \{C_1, C_2, \dots, C_m\}$ be an IN $[\mathrm{s}, t]$ cover of X, however, $C_i = \{\mathrm{T_{c,i}}, \mathrm{I_{c_i}}, F_{c_i}\}$ and $C_i \in lNS(i = 1,2, \dots, m)$. If $s = t = \beta$, then the IN $[\mathrm{s}, t]$ area of x is disturbed as an IN β region of x.

C. Parameter Optimizer using EHO Model

Finally, the hyperparameter selection of the INCRS model is performed by utilizing the EHO [20]. This model is chosen for its efficiency in balancing the exploration and exploitation stages, inspired by natural herding behaviour,

DOI: https://doi.org/10.54216/IJNS.270111

which helps avoid local optima and ensures global search capabilities. Compared to conventional optimization methods, such as grid or random search. The model also converges more quickly and requires fewer evaluations, thereby mitigating computational cost. Its population-based nature allows for a simultaneous search across various regions of the parameter space, thereby enhancing the likelihood of finding optimal hyperparameters. Furthermore, EHO demonstrates superior performance in diverse and complex optimization problems, making it suitable for fine-tuning the INCRS model to achieve higher classification accuracy and robustness in financial data analysis.

EHO is a meta-heuristic swarm-centred searching model that resolves a variety of optimization problems. This method simulates the herding behaviour of elephants. The EHO stages are explained as follows,

1. Produce individuals m and bifurcate the population into n clans. Subsequently, calculate the fitness value for each individual and arrange him or her in order of their fitness.

2. Upgrade each location on the clan c_n. Assume that the clan indicate c_n and the following location of each solution m in clan c_n

$$x_{new;c_n;m} \, {}^{1}\!/_{4} \, x_{c_n;m} \text{þ} a \times \text{ð} x_{best;c_n} - x_{c_n;m} \text{þ} \times c \tag{3}$$

Now, $x_{c_n;m}$ indicates the old location of solution m in the clan c_n, $x_{best;c_n}$ denotes the area of best solution in clan c_n and $x_{new;c_n;m}$ represents the newly upgraded location of solution m in clan c_n. a depicts the scaling factor which determines the effect of $x_{best;c_n}$ on $x_{c_n;m}$. c 2 [0, 1] indicates a random number from a uniform distribution. Select and retain the finest solution betwixt $x_{new;c_n;m}$ and $x_{c_n;m}$, utilizing Eq. (3).

3. Upgrade $x_{c;m}$and create $x_{new;c;m}$ to attain the best solution to employ Eq. (4) if the solution m's location corresponds to the finest position of solution ($x_{c_n;m} = x_{best;c_n}$). The fittest solution in each clan is upgraded:

$$x_{new;c_n;m} \, {}^{1}\!/_{4} \, b \times x_{center;c_n} \tag{4}$$

Now, b 2 [0, 1] denotes a factor which determines the effect of $x_{center;c_n}$ on $x_{new;c_n;m}$. On the other hand, the novel individual $x_{new;c_n;m}$ in Eq. (4) generates data gained by entire solutions from the clan c_n. Select and retain the finest solution betwixt $x_{new;c_n;m}$ and $x_{best;m}$. $x_{center;c_n}$ denotes the centre of the clan c_n, and for *the d* th dimension.

$$x_{center;c_n;d} \, {}^{1}\!/_{4} \, \frac{1}{N_{c_n}} \times \overset{X}{\underset{m^{1}/_{4}1}{N_{c_n x}}} \; c_n; m; d \tag{5}$$

Now, N_{c_n} indicates the Number of solutions in clan c_n. $1 \leq d \leq D$ represents d th dimension, D depicts its overall dimension.

4. Swapping the worst fitness individual in clan c_n to employ a separating operator,

$$X_{worst;c_n} 1/4 x_L \text{þ} \text{ð}_{XU} - x_L \text{þ} 1 \text{þ} \times r \tag{6}$$

Here, x_L signifies the lower bound of individual location, x_U is the Upper boundary of individual location and $x_{worst;c_n;m}$ refers to the worst individual in the clan c_n. And $r[0,1]$ indicates a sort of stochastic distribution together with a uniform distribution from the gamut of zero and one.

5. Using the recently upgraded locations, evaluate the population and gauge the fitness for each performance. Return the finest outcome (s_f) and the overall clans according to their value of fitness. The projected EHO pseudocode is displayed in Algorithm 1.

Algorithm 1: EHO pseudocode
Input: Dataset features Output: Optimized features Begin: Initialization: Create individuals; Dividing population into n clans; Compute fitness of every individual; Set generation counter $t = 1$ and maximal generation MaxGen.

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While $t < MaxGen$ do

Sort individuals according to their fitness.

Clan Upgrade:

For every clan c_n do

For each solution m in the clan c_n do

Upgrade $x_{c_n;m}$ and create $x_{new;c_n;m}$

Choose and retain the finest solution among $x_{c_n;m}$ and $x_{new;c_n;m}$

Upgrade $x_{best;m}$ and produce $x_{new;c_n;m}$

Choose the finest solution among $x_{bes;m}$ and $x_{new;c_n;m}$

end for

end for

For each clan, c_n population do

Substitute the poorest solution in the clan c_n

end for

Calculate population and fitness

end while

Return the finest solution to every clan

End

The fitness choice is a significant feature that influences the solution of the EHO model. The procedure of hyperparameter selection involves determining the optimal solution to assess the efficacy of the candidate result. The EHO model indicates accuracy as the primary standard for predicting the fitness function, as stated below.

$$Fitness = \max(P) \tag{7}$$

$$P = \frac{TP}{TP + FP} \tag{8}$$

While TP and FP signify the positive value of true and false.

4. Experimental Validation

The performance analysis of the ERPFFTS-INCRS model is examined under the metaverse financial transactions dataset [21]. The technique is simulated using Python 3.6.5 on a PC with an i5-8600k, 250GB SSD, GeForce 1050Ti 4GB, 16GB RAM, and 1TB HDD. Parameters include a learning rate of 0.01, ReLU activation, 50 epochs, a dropout rate of 0.5, and a batch size of 5. The dataset comprises 78,600 records, each representing a distinct metaverse financial transaction. Each record includes the following attributes: hour_of_day, timestamp, sending_address, receiving_address, transaction_type, amount, ip_prefix, age_group, login_frequency, location_region, purchase_pattern, risk_score, session_duration, and anomaly. The risk score is a key attribute and is assigned by utilizing a hybrid model; initially computed through an algorithm that evaluates transactional behaviours, amounts, frequency, and anomaly scores, followed by manual validation by domain experts to ensure contextual accuracy. Based on this, transactions are classified into three risk levels: low_risk (63,493), moderate_risk (8,611), and high_risk (6,495).

Table 1 and Fig. 3 illustrate the classifier outcome of the ERPFFTS-INCRS approach on 70:30. Based on 70% TRPHE, the ERPFFTS-INCRS model attains an average $accu_y$ of 98.77%, $prec_n$ of 96.20%, $reca_l$ of 95.36%, $F_{Measure}$ of 95.78%, and MCC of 94.15%. Similarly, at 30% TSPHE, the ERPFFTS-INCRS model achieves an average $accu_y$ of 98.67%, $prec_n$ of 96.05%, $reca_l$ of 94.91%, $F_{Measure}$ of 95.47%, and MCC of 93.70%.

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Table 1: Classifier outcome of ERPFFTS-INCRS model under 70:30

Classes	$Accu_y$	$Prec_n$	$Reca_l$	$F_{Measure}$	MCC
TRPHE (70%)					
Low_Risk	98.63	98.97	99.34	99.15	95.55
Moderate_Risk	98.44	93.69	91.94	92.80	91.94
High_Risk	99.24	95.96	94.82	95.38	94.97
Average	98.77	96.20	95.36	95.78	94.15
TSPHE (30%)					
Low_Risk	98.50	98.83	99.32	99.07	95.15
Moderate_Risk	98.28	93.15	91.18	92.15	91.20
High_Risk	99.22	96.16	94.23	95.19	94.76
Average	98.67	96.05	94.91	95.47	93.70

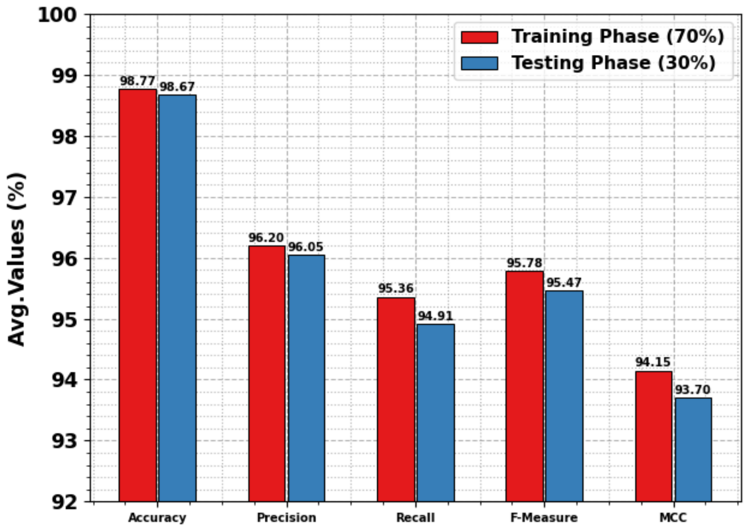

Figure 3. Average values of ERPFFTS-INCRS model (a) 70% TRPHE, and (b) 30%TSPHE

Fig. 4 exemplifies the training (TRAIN) $accu_y$ and validation (VALID) $accu_y$ of an ERPFFTS-INCRS technique over 25 epochs. At first, both TRAIN and VALID $accu_y$ rise rapidly, representing efficient pattern learning from the data. Around the epoch, the VALID $accu_y$ slightly exceeds the training accuracy, implying good generalization without overfitting. As training advances, it reflects maximum performance and a minimum performance gap between TRAIN and VALID. The close alignment of both curves during training suggests that the technique is well regularised and well-generalized. This exhibits the technique's stronger capability in learning and retaining valuable features across both seen and unseen data.

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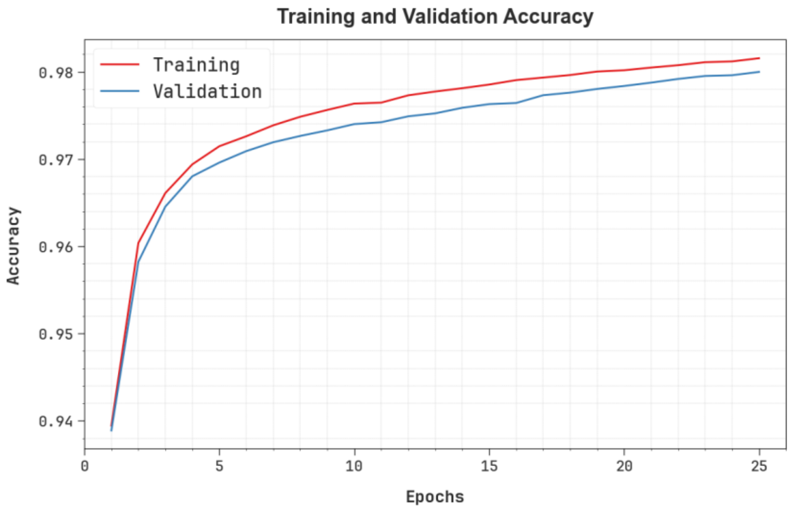

Figure 4. $Accu_y$ Curve of ERPFFTS-INCRS model

Fig. 5 demonstrates the TRAIN and VALID losses of the ERPFFTS-INCRS method over 25 epochs. Initially, both TRAIN and VALID losses are higher, showing that the process begins with a partial understanding of the data. As training evolves, both losses persistently decline, displaying that the method is efficiently learning and enhancing its parameters. The close alignment between the TRAIN and VALID loss curves during training suggests that the technique has not over-fitted and maintains good generalization to unseen data. This persistent and steady decrease in loss shows a stable, reliable, and well-trained DL model.

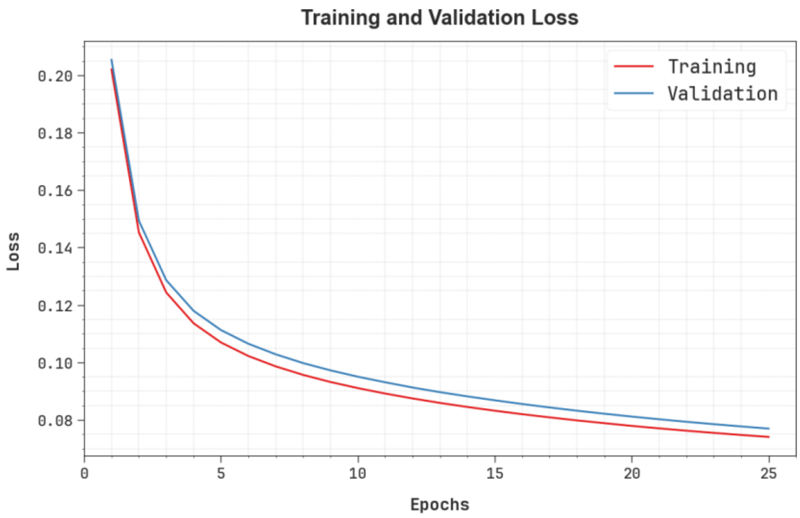

Figure 5. Loss curve of the ERPFFTS-INCRS method

In Fig. 6, the PR inspection study of the ERPFFTS-INCRS approach provides insights into its outcome by charting Precision against Recall for all classes. The outcomes display that the ERPFFTS-INCRS approach consistently achieves elevated PR values across different classes, demonstrating its proficiency in retaining a significant share of true positive predictions among all positive predictions (precision) while also capturing a substantial portion of actual positives (recall). The stable improvement in PR values across each class indicates the effectiveness of the ERPFFTS-INCRS model in the classification procedure.

DOI: https://doi.org/10.54216/IJNS.270111

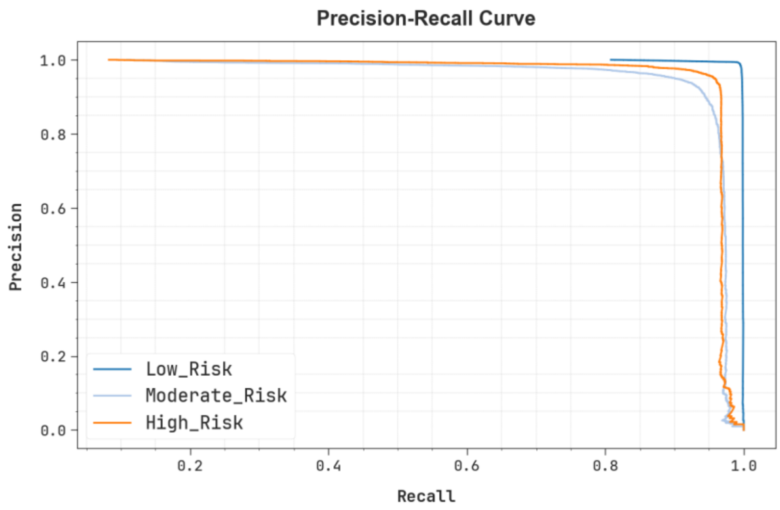

Figure 6. PR curve of ERPFFTS-INCRS method

In Fig. 7, the ROC analysis of the ERPFFTS-INCRS approach is presented. The outcomes indicate that the ERPFFTS-INCRS approach achieves elevated ROC values across all class labels, demonstrating considerable capabilities to distinguish between classes. This consistent pattern of increased values of ROC for several classes suggests the efficacious outcomes of the ERPFFTS-INCRS technique on class prediction, underscoring the robust nature of the classification process.

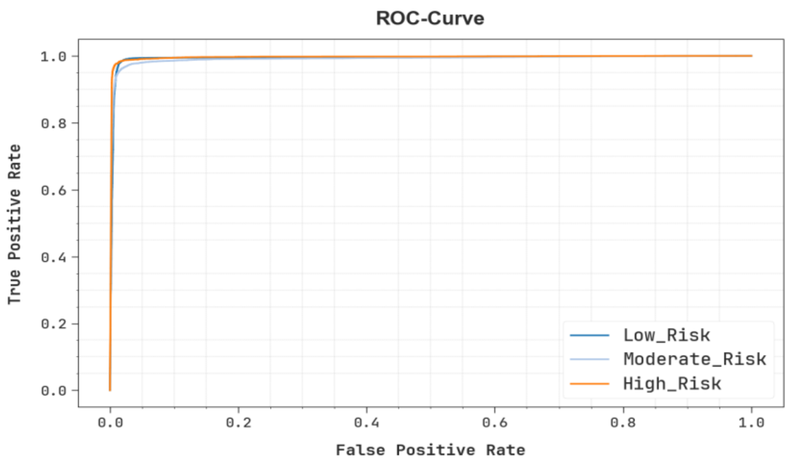

Figure 7. ROC curve of ERPFFTS-INCRS method

Table 2 and Fig. 8 present a comparative study of the ERPFFTS-INCRS approach with current methods under various metrics [22-24]. The table values emphasized that the ERPFFTS-INCRS model achieved higher cu_y, $prec_n$, $reca_l$, and $F_{Measure}$ of 98.77%, 96.20%, 95.36%, and 95.78%, respectively. While the present methodologies, namely logistic regression (LR), SVM, XGBoost, GraphSAGE, GGNN, random forest (RF), and GCN, have worse performance.

Table 2: Comparative analysis of ERPFFTS-INCRS model with existing techniques

Models	$Accu_y$	$Prec_n$	$Reca_l$	$F_{Measure}$
LR	77.85	85.36	78.43	87.79
SVM	93.86	80.96	94.25	89.82
XGBoost	92.19	95.55	85.41	94.32

DOI: https://doi.org/10.54216/IJNS.270111

GraphSAGE	91.66	94.80	77.36	91.01
GGNN	86.46	82.29	79.55	88.12
RF	83.77	88.11	77.05	88.85
GCN	95.54	94.32	87.32	92.66
ERPFFTS-INCRS	98.77	96.20	95.36	95.78

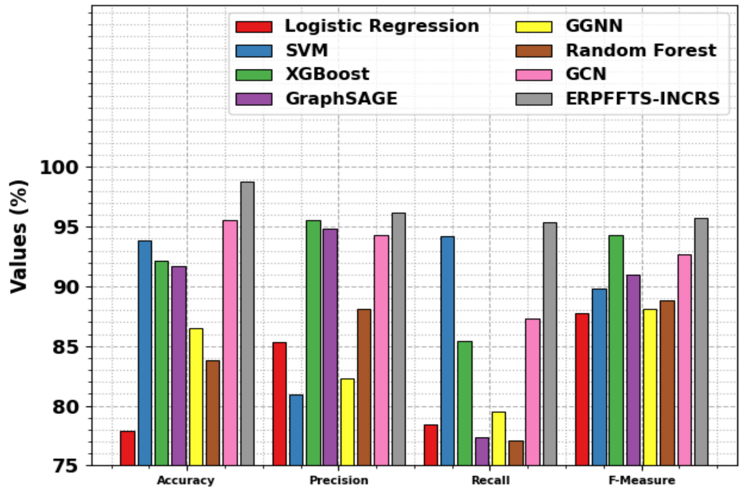

Figure 8. Comparative study of ERPFFTS-INCRS with existing techniques

In Table 3 and Fig. 9, the computational time (CT) of the ERPFFTS-INCRS model is compared to that of current approaches. The ERPFFTS-INCRS model offers a lower CT of 6.73sec while the LR, SVM, XGBoost, GraphSAGE, GGNN, RF, and GCN methodologies achieve superior CTs of 7.85sec, 16.72sec, 24.68sec, 29.90sec, 29.75sec, 25.77sec, and 21.74sec, respectively.

Table 3: CT outcome of ERPFFTS-INCRS model with recent methods

Models	**CT (sec)**
LR	7.85
SVM	16.72
XGBoost	24.68
GraphSAGE	29.90
GGNN	29.75
RF	25.77
GCN	21.74
ERPFFTS-INCRS	6.73

DOI: https://doi.org/10.54216/IJNS.270111

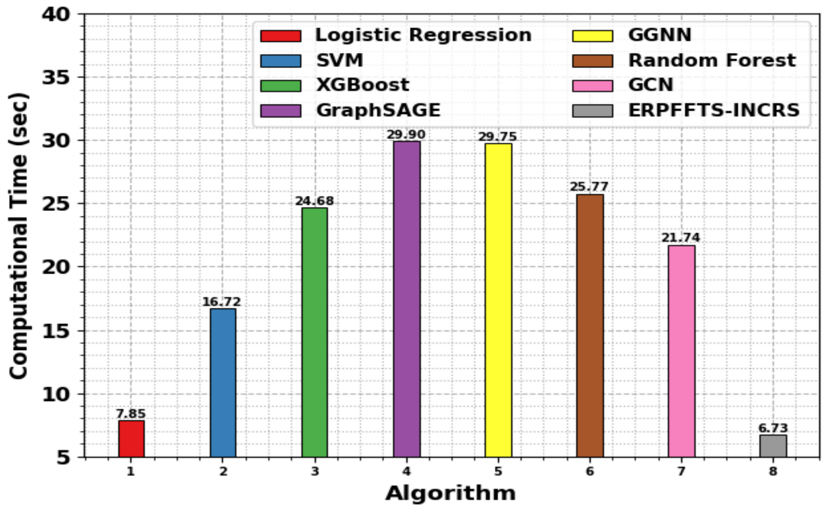

Figure 9. CT outcome of the ERPFFTS-INCRS model with recent methods

Table 4 and Fig. 10 illustrates the ablation study of the ERPFFTS-INCRS technique with existing models. The ablation study evaluates the efficiency of the ERPFFTS-INCRS technique by comparing it with existing methods such as the EHO and INCRS. The ERPFFTS-INCRS model attained an $accu_y$ of 98.77%, $prec_n$ of 96.20%, $reca_l$ of 95.36%, and $F_{Measure}$ of 95.78% across the dataset. In contrast, the INCRS method attained an $accu_y$ of 98.22%, $prec_n$ of 95.63%, $reca_l$ of 94.86%, and $F_{Measure}$ of 95.18%. The EHO method performed comparatively lower with an $accu_y$ of 97.54%, $prec_n$ of 95.00%, $reca_l$ of 94.18%, and $F_{Measure}$ of 94.65%. These results clearly illustrate that the ERPFFTS-INCRS model outperforms both baselines, confirming its robustness and improved detection capability.

Table 4: Result analysis of the ablation study of ERPFFTS-INCRS methodology

Methodology	$Accu_y$	$Prec_n$	$Reca_l$	$F_{Measure}$
EHO Algorithm	97.54	95.00	94.18	94.65
INCRS	98.22	95.63	94.86	95.18
ERPFFTS-INCRS	98.77	96.20	95.36	95.78

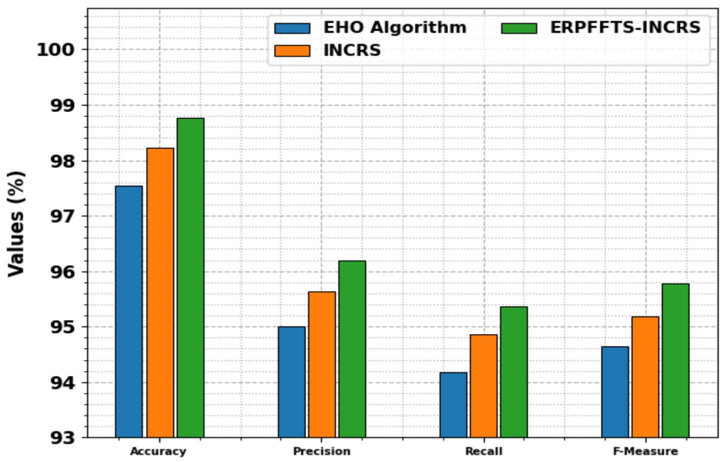

Figure 10. Result analysis of the ablation study of ERPFFTS-INCRS methodology

DOI: https://doi.org/10.54216/IJNS.270111

5. Conclusion

In this paper, an ERPFFTS-INCRS model is proposed. This paper aims to develop an effective risk prediction model for enhancing the reliability and security of BC financial transactions under uncertain conditions, utilizing neutrosophic approaches. Initially, the z-score standardization is used to clean, transform, and organize raw data into a structured and meaningful format. Afterwards, the ERPFFTS-INCRS model implements the INCRS method for the financial classification process. Finally, the hyperparameter selection of the INCRS method is implemented by the design of the EHO method. The experimental evaluation of the ERPFFTS-INCRS approach is examined under the MFT dataset. The comparison analysis of the ERPFFTS-INCRS approach revealed a superior accuracy value of 98.77% compared to existing methods.

Funding: "This research received no external funding"

Conflicts of Interest: "The authors declare no conflict of interest."

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