Bankruptcy Prediction using Diophantine Neutrosophic Number for Enterprise Resource Planning on Value of Accounting Information

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Abstract

Enterprise Resource Planning (ERP) is paramount in modern business, integrating many fundamental processes such as human resources, economics, customer relationship management, and supply chain management into a comprehensive infrastructure. Leveraging the wide-ranging data apprehended by ERP techniques, an organization could improve its financial analysis abilities, involving bankruptcy prediction. By using analytics methods like predictive modeling and machine learning, the ERP system could examine market trends, historical financial information, key performance indicators, and other related factors to evaluate the financial stability and health of the company. This prediction insight empowers businesses to vigorously detect advanced indicators of financial distress, alleviate risks, and make informed strategic decisions to avoid bankruptcy. Integrating bankruptcy prediction techniques within the ERP system allows organizations to reinforce contingency strategies, financial planning, and risk management, protecting long-term competitiveness and sustainability in a dynamic business environment. This study introduces a Bankruptcy Prediction using the Diophantine Neutrosophic Number for Enterprise Resource Planning (BPDNN-ERP) technique on the value of accounting information. The BPDNN-ERP technique begins with a harmony search algorithm (HSA) for electing feature subsets. In addition, the BPDNN-ERP technique applies the DNN model for the prediction of bankruptcies. To increase the performance of the DNN model, the manta ray foraging optimization (MRFO) model can be used. The experimental study demonstrated the enhanced performance of the BPDNN-ERP algorithm equated to existing forecasting methods

Keywords: Bankruptcy Prediction; Enterprise Resource Planning; Harmony Search Algorithm; MRFO; Diophantine Neutrosophic Number

1. Introduction

Fuzzy-set (FS) theory was used in numerous real issues in indefinite atmospheres. Thus, many experts examined numerous outcomes utilizing different ways of fuzzy-set theory, for example, interval valued FS and intuitionistic FS. These additions can contract with indefinite real issues. An intuitionistic FS can only capable to handle with imperfect data over its falsity and truth membership values, however it does not manage with indeterminate data. Therefore, the neutrosophic idea has been improved in order to overwhelm this issue. A neutrosophic set (NS) is a scientific concept serving problems such as indeterminate, imprecise and inconsistent data. Current research works on NS comprise a complex NS and single-valued NS. NS is highly suitable for managing indeterminate, incomplete and inconsistent data in real-time uses. Currently, numerous researchers were completed on NS, the

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most current existence on neutrosophic vague soft expert set, n-valued refined neutrosophic soft set, vague soft set, time-neutrosophic soft set and complex neutrosophic soft expert set.

Bankruptcy is a vital fragment of the functioning of firms in market economy circumstances [1]. On the one hand, it is standard, as opposition forces the bankruptcy of non-profit units and the formation of space for those utilizing rare resources more effectively. Where, each bankruptcy harms numerous stakeholders such as employees, creditors, consumers, suppliers, and the local community [2]. Particularly, the suppliers and creditors are exposed to the danger of loss when the defaulters go bankrupt. So, it is significant to conduct an inquiry into the forecast of bankruptcy danger. Early recognition of signs of fading economic conditions may permit taking helpful actions [3]. It can also avert sustaining damages by existing or potential capital suppliers. In the US, such exploration has been directed since the start of the 20th century, whereas in other developed countries it was introduced in the 70s of the preceding century [4]. It is an outcome of the fact that before the closure of the Soviet Union, these countries had a centrally deliberate economy, which in standard did not transport for the presence of the organization of bankruptcy. It was only in the early 1990s that the modification of the economy happened and 1st bankruptcy laws were introduced in the general of the preceding Eastern Bloc countries, tracked by initial bankruptcy measures [5]. Then, the researchers from these states started to be involved in the problem of measuring companies in the opinion of the danger of bankruptcy they face. The overview of effectual tools for business failure prediction in these countries permits to classify of possible bankruptcies and, so, decreases losses by evading collaboration with such entities [6]. Furthermore, these tools can perform as early warning methods besides bankruptcy and permit to recognition primary phases of a crisis. As an outcome, these firms may take initial recovery action to enhance their economic stand-up and to endure as a standard concern [7]. So, it is useful to analyze whether these countries perform bankruptcy danger valuations and what their level of development is.

The legitimacy and efficiency of this conventional statistical model depend mainly on a few restricting conventions like normality, linearity, independence between analyst variables, and a pre-existing efficient form linking the standard and forecaster variables [8]. These traditional models function best only when most arithmetical expectations are appropriate. Current research work in artificial neural networks (ANNs) displays that ANNs are great tools for pattern detection and classification owing to their non-linear nonparametric adaptive-learning assets [9]. ANN methods have already been employed effectively for numerous financial issues such as bankruptcy prediction [10].

Muslim et al. [11] proposed a combination method to enhance the precision of bankruptcy forecast dependent upon a GA-SVM and stacking ensemble model. This paper utilizes the Taiwanese Bankruptcy database. Next, a synthetic minority over-sampling method was executed for managing imbalance databases. The technique chooses the finest feature utilizing GA-SVM, adopts a novel approach by assembling the classifier, and utilizes XGBoost as a meta-learner. Jabeur and Serret [12] projected a united model for bankruptcy forecast dependent upon fsQCA and CNN approaches. Presently, CNNs are employed in numerous areas, and few areas are delivering greater performance when compared to traditional methods. In the developed model, a CNN employs standardized variables from fuzzy sets to enhance the performance of accuracy. Chandok et al. [13] projected a novel (WSODL-BPFCA) system. The technique uses the normalization of min-max to alter the input data into an even layout. For bankruptcy forecast, the technique presented an attention-based LSTM (ALSTM) technique.

Zhu et al. [14] suggest a new enterprise economic danger assessment and forecast method integrating SMOTE and Edited Nearest Neighbors (SMOTE-ENN) and Natural Gradient Boosting (NGBoost) technique. The CRITIC-TOPSIS model was initially applied. This model is employed to moderate the inequity in the amount of instances across dissimilar classes. Finally, NGBoost is employed to progress a forecasting method for business economic danger dependent upon the clustered data. Xiao et al. [15] intended a novel 3-phase decision support research structure. At first, an indicator screening approach is invented dependent upon economic risk classification capability to find the indicator method. Next, the combined weighting technique has been presented to measure economic danger. The game theory was used to discover the optimum distribution coefficient for solitary models. The LightGBM ensemble technique was used to perform real values forecast rather than identification. Wang et al. [16] produced a Stacking-based economic institution risk approval technique. Moreover, a bank approval system is built utilizing a DL system on a biased dataset; with a feature extractor executed utilizing CNN and feature-based counterfactual expansion. Lastly, the technique enhances the method by picking the optimum co-efficient of loss function dependent upon the aspects and outcomes of the bank approval method.

This study introduces a Bankruptcy Prediction using the Diophantine Neutrosophic Number for Enterprise Resource Planning (BPDNN-ERP) technique on the value of accounting information. The BPDNN-ERP technique begins with a harmony search algorithm (HSA) for electing feature subsets. In addition, the BPDNN-ERP technique applies the DNN model for the prediction of bankruptcies. To increase the performance of the DNN technique, the manta ray foraging optimization (MRFO) algorithm can be used. The experimental study

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demonstrated the enhanced performance of the BPDNN-ERP methodology equated to existing forecasting methods.

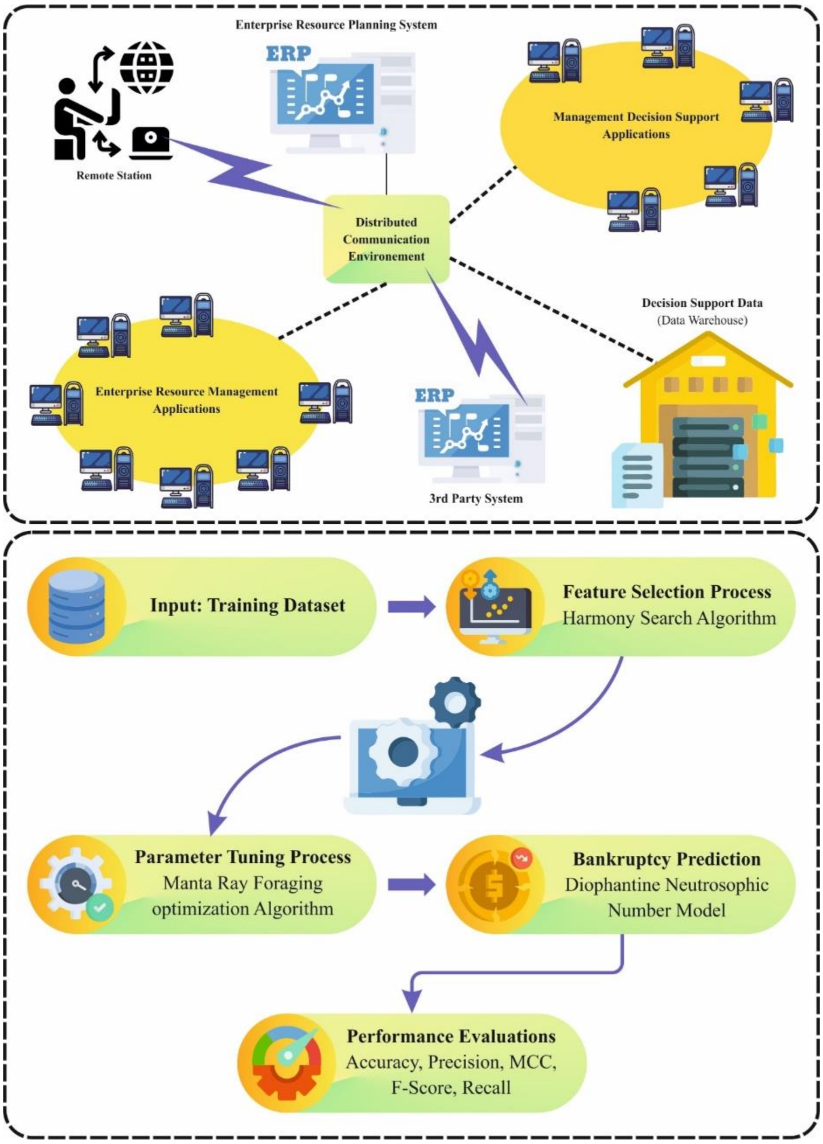

Figure 1: Overall flow of BPDNN-ERP technique

2. Proposed Methodology

In this study, we have presented a BPDNN-ERP system on the value of accounting information. The main objective of the BPDNN-ERP technique contains different kinds of processes involved as feature selection using HSA, DNN-based forecast, and MRFO-based hyperparameter tuning. Fig. 1 demonstrates the entire flow of BPDNN-ERP system.

A. Dimensionality Reduction using HSA

The BPDNN-ERP technique begins with HSA for electing feature subsets. HSA is a new swarm intelligence metaheuristic technique depends on the observation that the music construction aims to discover a best state of harmony [17]. The major reasons behind the efficiency and broadly accepted HSA are Intensification and divergence of solution space. HSA is used to improve the coefficients or parameters attained from the ARIMA model. Fig. 2 represents the flowchart of HAS. The parameter of HSA is defined below:

Harmony Memory Consideration Rate (HMCR): HMCR $\in [0,1]$ and is the probability of choosing a harmony existing in HM.

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HM: The place where harmony is kept.

HM Size (HMS): Overall amount of solution vectors existing in HM.

Randomization ($rand$): Randomization is also a crucial parameter to increase the diversity of the solution. Pitch Adjusting Rate (PAR): PAR ∈ [0,1] and is the adjustment degree.

The randomization probability is presented by $rand = 1 - \text{HMCR}$.

No. of Improvisations (NI): The solutions amount produced for every iteration.

Bandwidth (BW): the amount of alterations permitted in pitch adjustment was represented as Bandwidth. In general, BW values are kept constantly low for better exploration and finetuning. The steps of the HSA are:

Initialization of parameter.

Arbitrarily pick a candidate within the solution space to generate HM.

Produce a candidate solution $x = (x_1, x_2, \dots, x_n)$ by

$$x_i = \begin{cases} x_i(old) & if\ r_1 \leq HMCR \\ x_i(new) \in [U_i, L_i] & otherwise, \end{cases} \tag{1}$$

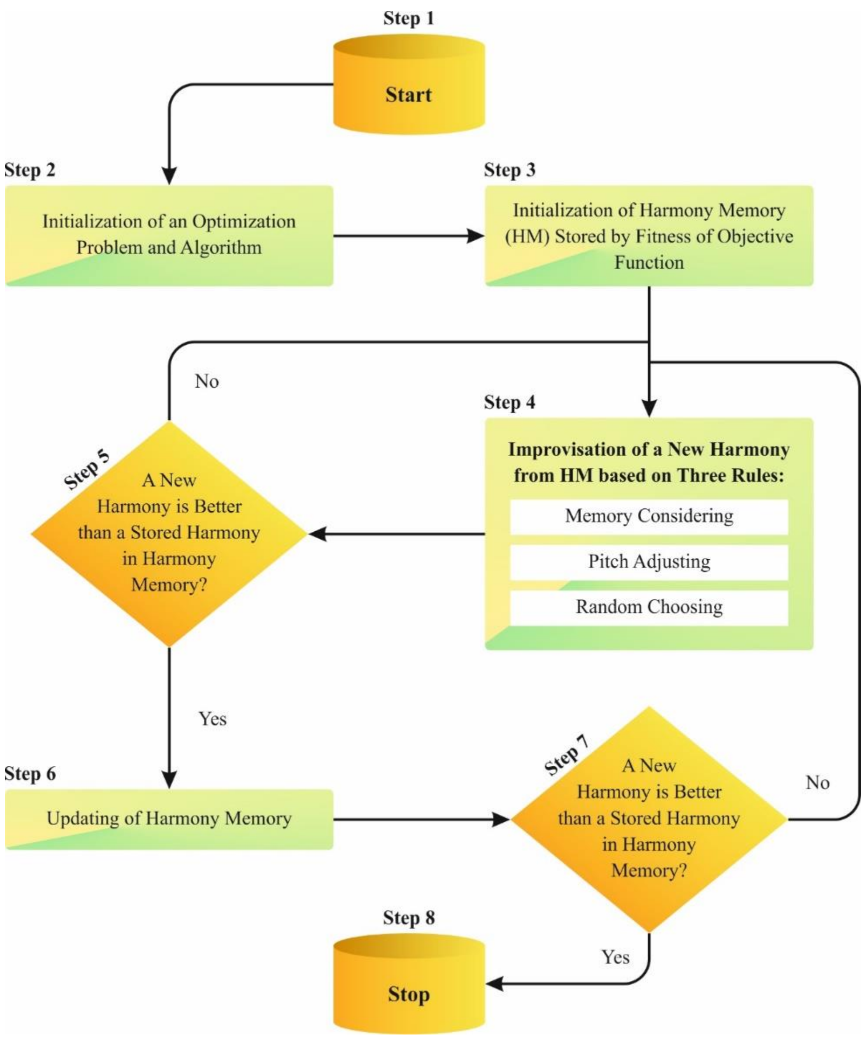

Figure 2: Flowchart of HSA

In Eq. (1), $x_i(new)$ denotes the novel solution produced by linear adjustment, $x_i(old)$ refers to the harmony pre-existing in HM and the uniformly distributed random value within [0,1] is r_1.

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$$x_i(new) = \begin{cases} x_i(new) + r_3 * BW & if\ r_2 \le PAR \\ x_i(\text{new}) & otherwise, \end{cases} \quad (2)$$

In Eq. (2), r_2, r_3 random value within [0,1] and BIV indicates the value of bandwidth.

If $f(x_{new}) \le f(x_{old})$ the HM is updated by substituting the old harmony with a novel one.

Repeat steps 3 and 4 until the iteration is obtained.

In the HSA method, the objectives have been combined into a single objective formulation such that an existing weight classifies every objective significance [18]. In this paper, we assume an FF which unites both the objectives of FS that defined in (3).

$$Fitness(X) = \alpha \cdot E(X) + \beta * \left(1 - \frac{|R|}{|N|}\right) \quad (3)$$

Here, Fitness(X) signifies the value of fitness of a sub-set X, $E(X)$ represents the classifier rate of error by utilizing the nominated feature from X sub-set, $|R|$ and $|N|$ are the integer of nominated feature and the amount of original feature in the data, β and α are the weights of reduction percentage and classification error, $\alpha \in [0,1]$ and $\beta = (1-\alpha)$.

B. DNN Model Architecture

Nest, the BPDNN-ERP technique applies the DNN model for the prediction of bankruptcies. In this section, we review the significant descriptions for further learning [19].

Consider $\mathcal{X}$ as a universal. The PIVFS $L = \{\tau, \langle \widetilde{\Psi_L^{\mathcal{T}}}(\tau), \widetilde{\Psi_L^{\mathcal{F}}}(\tau) \rangle | \tau \in \mathcal{X}\}$, For $\widetilde{\Psi_L^{\mathcal{T}}}: \mathcal{X} \to Int([0,1])$ and $\widetilde{\Psi_L^{\mathcal{F}}}: \mathcal{X} \to Int([0\ and 1])$ are the MD and NMD of $\tau \in \mathcal{X}$ to the set L, correspondingly, and $0 \le (\Psi_L^{\mathcal{T}}(\tau))^2 + (\Psi_L^{\mathcal{F}}(\tau))^2 \le 1$. For simplicity, $L = \langle [\Psi_L^{\mathcal{T}}, \Psi_L^{\mathcal{T}}], [\Psi_L^{\mathcal{F}}, \Psi_L^{\mathcal{F}}] \rangle$ is known as a PyIVFN.

The NS $L = \{x, \langle \Psi_L^{\mathcal{T}}(\tau), \Psi_L^{\mathcal{I}}(\tau), \Psi_L^{\mathcal{F}}(\tau) \rangle | \tau \in \mathcal{X}\}$, For $\Psi_L^{\mathcal{T}}: \mathcal{X} \to [0,1]$, $\Psi_L^{\mathcal{I}}: \mathcal{X} \to [0\ and\ 1]$ and $\Psi_L^{\mathcal{F}}: \mathcal{X} \to [0\ and\ 1]$ is the positive MD (PMD), neutral and negative MDs (NMD)of $\tau \in \mathcal{X}$, correspondingly and $0 \le (\Psi_L^{\mathcal{T}}(\tau)) + (\Psi_L^{\mathcal{I}}(\tau)) + (\Psi_L^{\mathcal{F}}(\tau)) \le 2$. For simplicity $M = \langle \Psi_L^{\mathcal{T}}, \Psi_L^{\mathcal{I}}, \Psi_L^{\mathcal{F}} \rangle$ is known as a neutrosophic number (NN).

The Pythagorean NS $L = \{\tau, \langle \Psi_L^{\mathcal{T}}(\tau), \Psi_L^{\mathcal{I}}(\tau), \Psi_L^{\mathcal{F}}(\tau) \rangle | \tau \in \mathcal{X}\}$, while $\Psi_L^{\mathcal{T}}: \mathcal{X} \to [0,1]$, $\Psi_L^{\mathcal{I}}: \mathcal{X} \to [0\ and\ 1]$ and $\Psi_L^{\mathcal{F}}: \mathcal{X} \to [0\ and\ 1]$ represents the PMD, neutral MD and NMDs of $\tau \in \mathcal{X}$, correspondingly and $0 \le (\Psi_L^{\mathcal{T}}(\tau))^2 + (\Psi_L^{\mathcal{I}}(\tau))^2 + (\Psi_L^{\mathcal{F}}(\tau))^2 \le 2$. For $M = \langle \Psi_L^{\mathcal{T}}, \Psi_L^{\mathcal{I}}, \Psi_L^{\mathcal{F}} \rangle$ are the Pythagorean neutrosophic number (PyNN).

The DNN concept is discussed. Thus, the DNN and operations are determined.

The Pythagorean DNN set (PyDNS)

$L = \{\tau, \langle (\Psi_L^{\mathcal{T}}(\tau), \Psi_L^{\mathcal{I}}(\tau), \Psi_L^{\mathcal{F}}(\tau)), (\varsigma(\tau)) \rangle | \tau \in \mathcal{X}\}$, for $\Psi_L^{T}: \mathcal{X} \to [0\ and\ 1]$, $\Psi_L^{I}: \mathcal{X} \to [0\ and\ 1]$ and $\Psi_L^{F}: \mathcal{X} \to [0\ and\ 1]$ are the PMD, neutral MD and NMD of $x \in \mathcal{X}$ to L, correspondingly and $0 \le (\varsigma(\tau)\Psi_L^{\mathcal{T}}(\tau))^2 + (\varsigma(\tau)\Psi_L^{\mathcal{I}}(\tau))^2 + (\varsigma(\tau)\Psi_L^{\mathcal{F}}(\tau))^2 \le 2$, whereas, $\varsigma \in [0,1$. For simplicity, $L = \langle (\Psi_L^{\mathcal{T}}, \Psi_L^{\mathcal{I}}, \Psi_L^{\mathcal{F}}), \varsigma \rangle$ denotes the PyDNN.

The new type of DNS $L = \{\tau, \langle (\Psi_L^{\mathcal{T}}(\tau), \Psi_L^{\mathcal{I}}(\tau), \Psi_L^{\mathcal{F}}(\tau)), (\varsigma(\tau)) \rangle | x \in \mathcal{X}\}$, while $\Psi_L^{T}: \mathcal{X} \to [0\ and\ 1]$, $\Psi_L^{I}: \mathcal{X} \to [0,1]$ and $\Psi_L^{F}: \mathcal{X} \to [0,1]$ are the PMD, neutral MD and NMD of $x \in \mathcal{X}$ to L, correspondingly and $0 \le (\varsigma(\tau)\Psi_L^{\mathcal{T}}(\tau))^{\aleph} + (\varsigma(\tau)\Psi_L^{\mathcal{I}}(\tau))^{\aleph} + (\varsigma(\tau)\Psi_L^{\mathcal{F}}(\tau))^{\aleph} \le 2$, where, $\varsigma \in [0,1]$ and $\aleph \ge 1$. For simplicity, $L = \langle (\Psi_L^{\mathcal{T}}, \Psi_L^{\mathcal{I}}, \Psi_L^{\mathcal{F}}), \varsigma) \rangle$ denote a novel kind of DNN.

Consider $L = \{(\Psi^{\mathcal{T}}, \Psi^{\mathcal{I}}, \Psi^{\mathcal{F}}), \varsigma\}$, $L_1 = \{(\Psi_1^{\mathcal{T}}, \Psi_1^{\mathcal{I}}, \Psi_1^{\mathcal{F}}), \varsigma\}$ and $L_2 = \{(\Psi_2^{\mathcal{T}}, \Psi_2^{\mathcal{I}}, \Psi_2^{\mathcal{F}}), \varsigma\}$ are new kinds of DNNs, and $\aleph > 0$. Thus,

$$1.\ L_1 \uplus L_2 = \begin{bmatrix} \sqrt[\aleph]{(\varsigma\Psi_1^{\mathcal{T}})^{\aleph} + (\varsigma\Psi_2^{\mathcal{T}})^{\aleph} - (\varsigma\Psi_1^{\mathcal{T}})^{\aleph} \cdot (\varsigma\Psi_2^{\mathcal{T}})^{\aleph}}, \\ \sqrt[\aleph]{(\varsigma\Psi_1^{\mathcal{I}})^{\aleph} + (\varsigma\Psi_2^{\mathcal{I}})^{\aleph} - (\varsigma\Psi_1^{\mathcal{I}})^{\aleph} \cdot (\varsigma\Psi_2^{\mathcal{I}})^{\aleph}}, \\ \varsigma\Psi_1^{\mathcal{F}} \cdot \varsigma\Psi_2^{\mathcal{F}} \end{bmatrix},$$

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2. $L_1 \otimes L_2 = \begin{bmatrix} \varsigma\Psi_1^{\mathcal{T}} \cdot \varsigma\Psi_2^{\mathcal{T}}, \\ \sqrt[\aleph]{(\varsigma\Psi_1^{\mathcal{I}})^{\aleph} + (\varsigma\Psi_2^{\mathcal{I}})^{\aleph} - (\varsigma\Psi_1^{\mathcal{I}})^{\aleph} \cdot (\varsigma\Psi_2^{\mathcal{I}})^{\aleph}}, \\ \sqrt[\aleph]{(\varsigma\Psi_1^{\mathcal{F}})^{\aleph} + (\varsigma\Psi_2^{\mathcal{F}})^{\aleph} - (\varsigma\Psi_1^{\mathcal{F}})^{\aleph} \cdot (\varsigma\Psi_2^{\mathcal{F}})^{\aleph}} \end{bmatrix}$

3. $\aleph \cdot L = [\sqrt[\aleph]{1-(1-(\varsigma\Psi^{\mathcal{T}})^{\aleph})^{\aleph}}, \sqrt[\aleph]{1-(1-(\varsigma\Psi^{\mathcal{I}})^{\aleph})^{\aleph}}, (\varsigma\Psi^{\mathcal{F}})^{\aleph}]$,

4. $L^{\aleph} = [(\varsigma\Psi^{\mathcal{T}})^{\aleph}, \sqrt[\aleph]{1-(1-(\varsigma\Psi^{\mathcal{I}})^{\aleph})^{\aleph}}, \sqrt[\aleph]{1-(1-(\varsigma\Psi^{\mathcal{F}})^{\aleph})^{\aleph}}]$.

The ED and HD measures are introduced for a new kind of DNNs.

Consider $L_1 = \{(\Psi_1^{\mathcal{T}}, \Psi_1^{\mathcal{I}}, \Psi_1^{\mathcal{F}}), \varsigma\rangle$ and $L_2 = \{(\Psi_2^{\mathcal{T}}, \Psi_2^{\mathcal{I}}, \Psi_2^{\mathcal{F}}), \varsigma\rangle$. Then

$$\mathcal{D}_E(L_1, L_2) = \frac{1}{2}\sqrt{\begin{bmatrix} \frac{1+(\varsigma\Psi_1^{\mathcal{T}})^2-(\varsigma\Psi_1^{\mathcal{I}})^2-(\varsigma\Psi_1^{\mathcal{F}})^2}{2} \\ -\frac{1+(\varsigma\Psi_2^{\mathcal{T}})^2-(\varsigma\Psi_2^{\mathcal{I}})^2-(\varsigma\Psi_2^{\mathcal{F}})^2}{2} \end{bmatrix}^2 + \frac{1}{2}\begin{bmatrix} \frac{1+(\varsigma\Psi_1^{\mathcal{T}})^2-(\varsigma\Psi_1^{\mathcal{I}})^2-(\varsigma\Psi_1^{\mathcal{F}})^2}{2} \\ -\frac{1+(\varsigma\Psi_2^{\mathcal{T}})^2-(\varsigma\Psi_2^{\mathcal{I}})^2-(\varsigma\Psi_2^{\mathcal{F}})^2}{2} \end{bmatrix}^2}$$

Here, $\mathcal{D}_E(L_1, L_2)$ denotes the ED amongst L_1 and L_2.

$$\mathcal{D}_H(L_1, L_2) = \frac{1}{2}\begin{bmatrix} \left| \frac{1+(\varsigma\Psi_1^{\mathcal{T}})^2-(\varsigma\Psi_1^{\mathcal{I}})^2-(\varsigma\Psi_1^{\mathcal{F}})^2}{2} - \frac{1+(\varsigma\Psi_2^{\mathcal{T}})^2-(\varsigma\Psi_2^{\mathcal{I}})^2-(\varsigma\Psi_2^{\mathcal{F}})^2}{2} \right| \\ +\frac{1}{2}\left| \frac{1+(\varsigma\Psi_1^{\mathcal{T}})^2-(\varsigma\Psi_1^{\mathcal{I}})^2-(\varsigma\Psi_1^{\mathcal{F}})^2}{2} - \frac{1+(\varsigma\Psi_2^{\mathcal{T}})^2-(\varsigma\Psi_2^{\mathcal{I}})^2-(\varsigma\Psi_2^{\mathcal{F}})^2}{2} \right| \end{bmatrix}$$

Here, $\mathcal{D}_H(L_1, L_2)$ denotes the HDs among L_1 and L_2.

Here, $(\mathcal{D}_E(L_1, L_2) + \mathcal{D}_E(L_2, L_3))^2$ suggests

$$\frac{1}{4}((O-P)^2+\frac{1}{2}(O-P)^2)+\frac{1}{4}((P-Q)^2+\frac{1}{2}(P-Q)^2)$$

$$+\frac{1}{2}(\sqrt{(O-P)^2+\frac{1}{2}(O-P)^2} \times \sqrt{(P-Q)^2+\frac{1}{2}(P-Q)^2}),$$

Where

$$O = \frac{1+(\varsigma\Psi_1^{\mathcal{T}})^2-(\varsigma\Psi_1^{\mathcal{I}})^2-(\varsigma\Psi_1^{\mathcal{F}})^2}{2},$$

$$P = \frac{1+(\varsigma\Psi_2^{\mathcal{T}})^2-(\varsigma\Psi_2^{\mathcal{I}})^2-(\varsigma\Psi_2^{\mathcal{F}})^2}{2},$$

$$Q = \frac{1+(\varsigma\Psi_3^{\mathcal{T}})^2-(\varsigma\Psi_3^{\mathcal{I}})^2-(\varsigma\Psi_3^{\mathcal{F}})^2}{2}.$$

Therefore, $(\mathcal{D}_E(L_1, L_2) + \mathcal{D}_E(L_2, L_3))^2$

$$\geq \frac{1}{4}((O-P)^2+\frac{1}{2}(O-P)^2)+\frac{1}{4}((P-Q)^2+\frac{1}{2}(P-Q)^2)$$

$$+\frac{1}{2}((O-P)\times(P-Q)+\frac{1}{2}(O-P)\times(P-Q))$$

$$= \frac{1}{4}((O-P)^2+(P-Q)^2+2(O-P)\times(P-Q))$$

$$+\frac{1}{4}(\frac{1}{2}(O-P)^2+\frac{1}{2}(P-Q)^2+(O-P)\times(P-Q))$$

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$$= \frac{1}{4}(O - P + P - Q)^2 + \frac{1}{8}(O - P + P - Q)^2$$

$$= \frac{1}{4}[(O - Q)^2 + \frac{1}{2}(O - Q)^2]$$

$$= \mathcal{D}_E(L_1, L_3)^2.$$

C. MRFO-based Parameter Tuning

To enhance the performance of the DNN system, the MRFO model can be utilized. MRFO is a novel meta-heuristic technique that inspires the foraging behaviors of marine creatures named manta rays (MR) [20]. MRs contain 3 foraging approaches such as somersault, chain, and cyclone foraging. These foraging approaches can be unique, which stimulates this optimizer method.

1) CHAIN FORAGING

The MRs position the foraging chain as a line using attached their tails and heads. MRFO numbers that the better performance has the maximum focus on plankton which is the preferred food for MRs. This exemplifies the exploration of the method. The mathematical formula of chain foraging is as follows:

$$\begin{cases} x_i^t + r * (x_{best}^t - x_i^t) + \gamma * (x_{best}^t - x_i^t), \\ \quad i = 1 \\ x_i^t + r * (x_{i-1}^t - x_i^t) + \gamma * (x_{best}^t - x_i^t), \\ \quad i = 2,3, .. NP \end{cases} \tag{4}$$

$$\gamma = 2 * r * \sqrt{|\log(r)|} \tag{5}$$

2) CYCLONE FORAGING

If the focus on plankton is extremely high, MR not only method long foraging chains followed by moving nearby food among them move nearby the food beside a spiral path. This signifies the exploitation of the method.

$$x_i^{t+1} = \begin{cases} x_{best}^t + r * (x_{best}^t - x_i^t) + \omega * (x_{best}^t - x_i^t), \\ \quad i = 1 \\ x_{best}^t + r * (x_{i-1}^t - x_i^t) + \omega * (x_{best}^t - x_i^t), \\ \quad i = 2,3, \ldots NP \end{cases} \tag{6}$$

$$\omega = 2 * \exp(r * \frac{It\max - It + 1}{It\max}) * \sin(2\pi r) \tag{7}$$

3) SOMERSAULT FORAGING

In this method, the food position has been assumed that a pivot place. All the individuals turn near this pivot followed by appearing for the following position. The mathematical expression of somersault foraging is defined in Eq. (8):

$$x_i^{t+1} = x_i^t + S * (r2 * x_{best}^t - r3 * x_i^t), i = 1,2, .. NP \tag{8}$$

whereas S denotes the somersault feature.

The FF is the significant factor influencing the performance of the MRFO approach. The hyperparameter range procedure contains the solution encoder method to evaluate the efficiency of candidate outcomes. During this case, the MRFO reflects accuracy as the main standard to project FF, which can be expressed as below.

$$Fitness = \max(P) \tag{9}$$

$$P = \frac{TP}{TP + FP} \tag{10}$$

Whereas, TP specifies the true positive and FP denotes the false positive values.

3. Experimental Validation

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This section inspects the performance of the BPDNN-ERP model on the examined dataset. It covers 200 samples with 2 classes as definite in Table 1.

Table 1: Details of the dataset

Classes	No. of Samples
Bankrupt	100
Non-Bankrupt	100
Total Samples	200

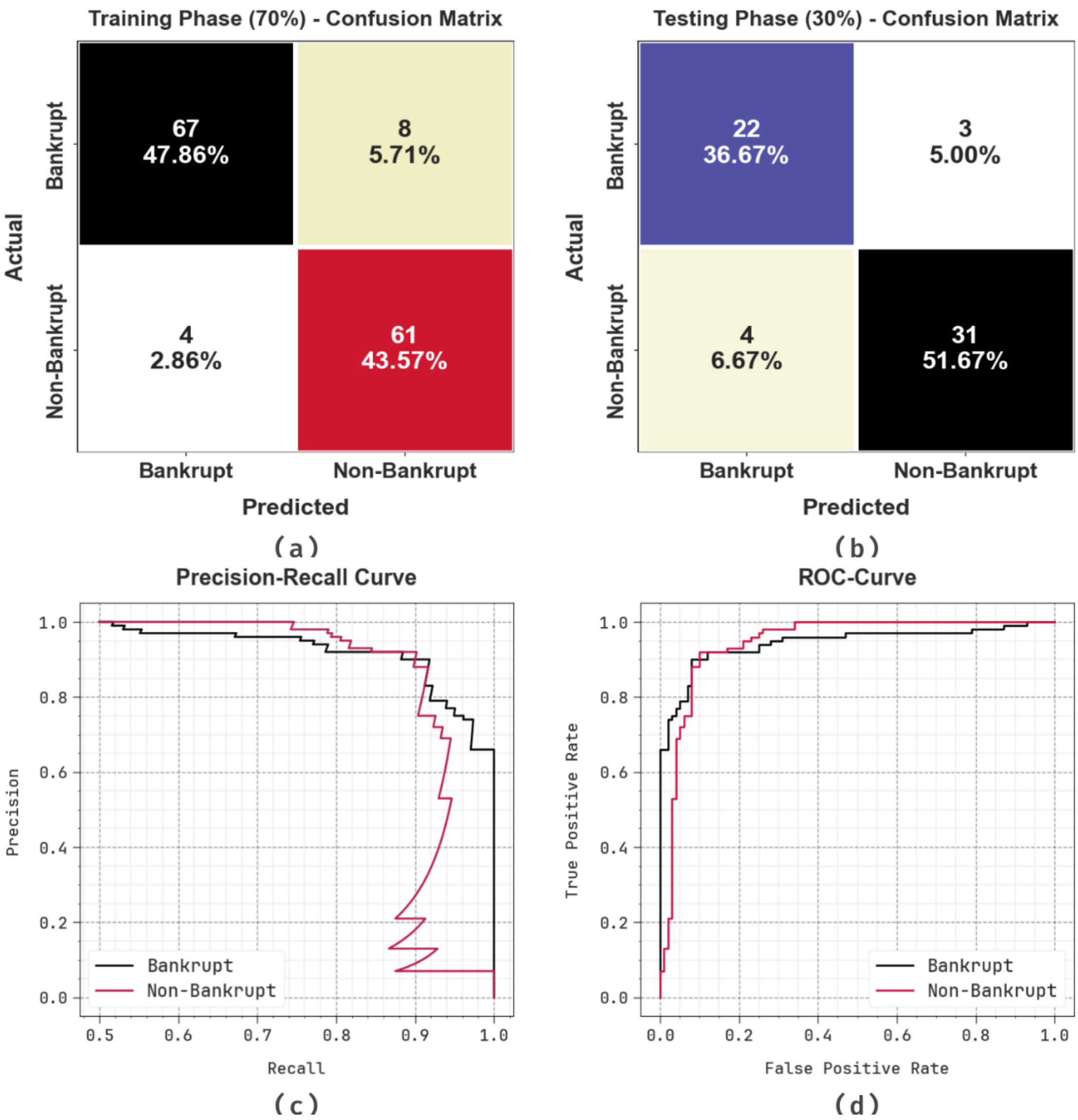

Figure 3: Classifier outcomes of (a-b) 70% and 30% of confusion matrices and (c-d) PR and ROC curves

Fig. 3 establishes the classifier results of the BPDNN-ERP model under the test data. Figs. 3a-3b represents the confusion matrices presented by the BPDNN-ERP technique on 70% of TRAS and 30% of TESS. The result implied that the BPDNN-ERP system has recognized and categorized all 2 class labels. Then, Fig. 3c establishes the PR study of the BPDNN-ERP approach. The figure designated that the BPDNN-ERP system has attained the highest performance of PR under all classes. Lastly, Fig. 3d demonstrates the ROC curve of the BPDNN-ERP

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method. The result shows that the BPDNN-ERP approach has resulted in capable results with the greatest ROC values at different class labels.

The prediction results of the BPDNN-ERP system are delivered in Table 2. Fig. 4 demonstrates the classifier result of the BPDNN-ERP model under 70%TRAS. The results suggest that the BPDNN-ERP model properly identified dual classes. On bankrupt class, the BPDNN-ERP model gets $accu_y$ of 89.33%, $prec_n$ of 94.37%, $reca_l$ of 89.33%, F_{score} of 91.78%, and MCC of 82.98%, correspondingly. Moreover, in the non-bankrupt class, the BPDNN-ERP approach gets $accu_y$ of 93.85%, $prec_n$ of 88.41%, $reca_l$ of 93.85%, F_{score} of 91.04%, and MCC of 82.98%, respectively.

Fig. 5 demonstrates the classifier result of the BPDNN-ERP method below under 30%TESS. The outcomes denote that the BPDNN-ERP model correctly recognized dual classes. On bankrupt class, the BPDNN-ERP approach gets $accu_y$ of 88.00%, $prec_n$ of 84.62%, $reca_l$ of 88.00%, F_{score} of 86.27%, and MCC of 76.18%, correspondingly. Moreover, in the non-bankrupt class, the BPDNN-ERP approach gets $accu_y$ of 88.57%, $prec_n$ of 91.18%, $reca_l$ of 88.57%, F_{score} of 89.86%, and MCC of 76.18%, respectively.

Table 2: Prediction outcome of BPDNN-ERP technique under 70% of TRAS and 30% of TESS

Classes	$Accu_y$	$Prec_n$	$Reca_l$	F_{Score}	MCC
TRAS (70%)					
Bankrupt	89.33	94.37	89.33	91.78	82.98
Non-Bankrupt	93.85	88.41	93.85	91.04	82.98
Average	91.59	91.39	91.59	91.41	82.98
TESS (30%)					
Bankrupt	88.00	84.62	88.00	86.27	76.18
Non-Bankrupt	88.57	91.18	88.57	89.86	76.18
Average	88.29	87.90	88.29	88.06	76.18

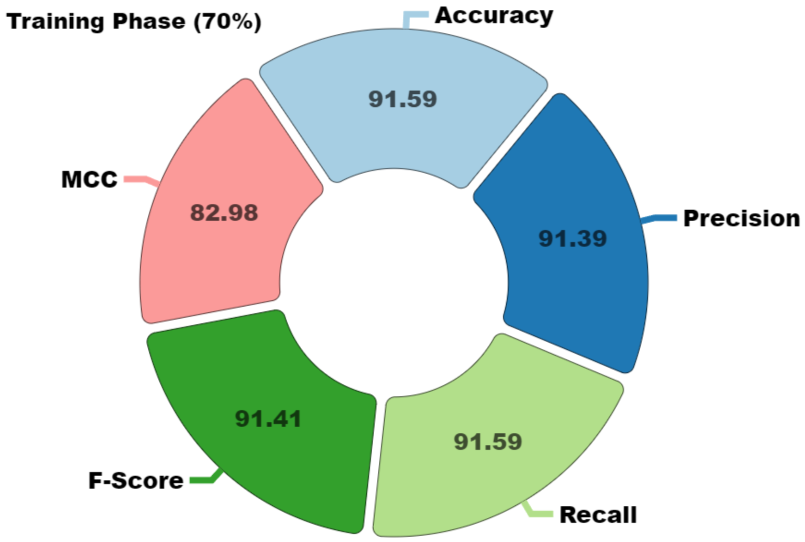

Figure 4: Average of BPDNN-ERP technique under 70%TRAS

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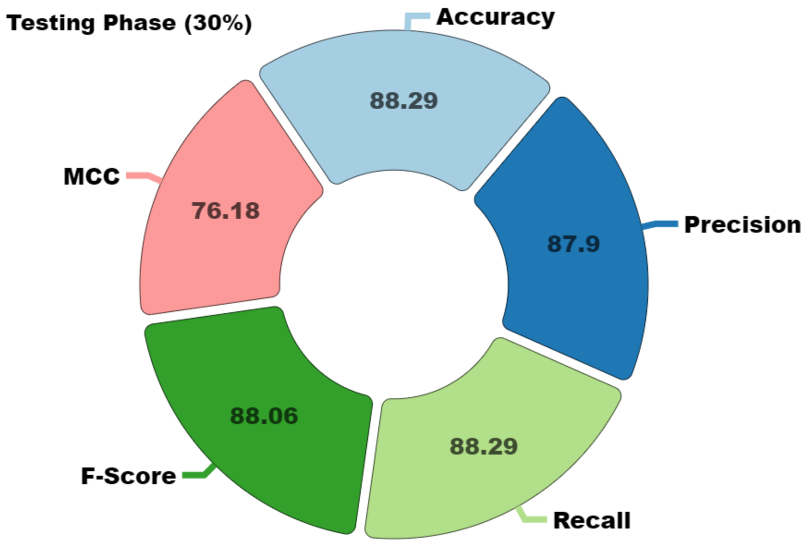

Figure 5: Average of BPDNN-ERP technique under 30%TESS

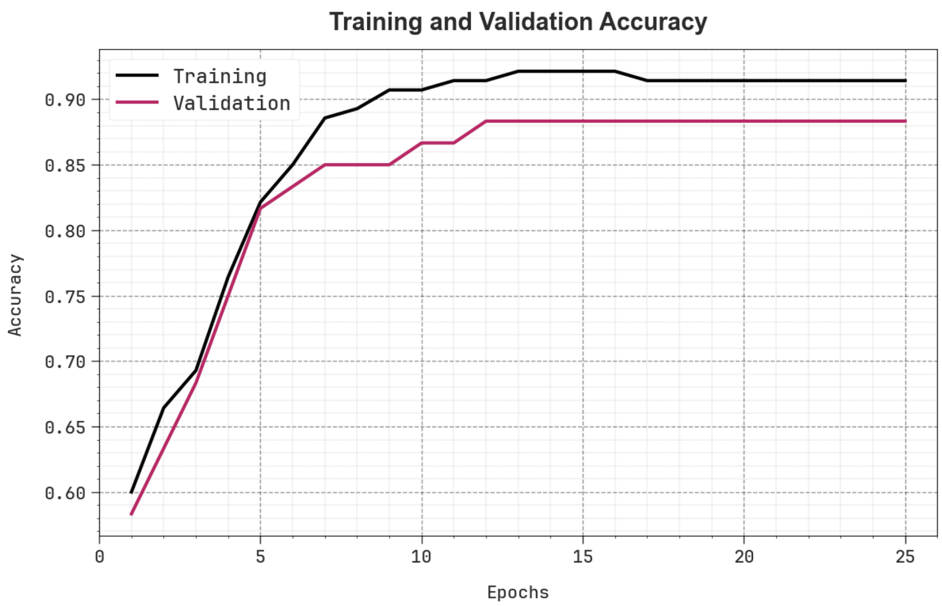

Figure 6: $Accu_y$ curve of the BPDNN-ERP technique

The performance of the BPDNN-ERP system is provided in Fig. 6 in the manner of validation accuracy (VALA) and training accuracy (TRAA) outcome. The result shows valuable clarification into the behavior of the BPDNN-ERP method over many epoch counts, signifying its learning method and general proficiencies. Mainly, the outcome concludes a stable development from VALA and TRAA with a development in epochs. It safeguards the adaptive nature of BPDNN-ERP method in the pattern recognition process on both the data. The expanding tendency in VALA summaries the aptitude of the BPDNN-ERP technique to regulate to the TRA data and shine in delivering precise identification of unseen data, representing robust general skills.

Fig. 7 establishes a complete representation of the validation loss (VALL) and training loss (TRLA) results of the BPDNN-ERP model over dissimilar epochs. The progressive decrease in TRLA emphasises the BPDNN-ERP technique improving the weights and diminishing the error of classification on both the data. The result specifies a clear understanding of the BPDNN-ERP system relation with TRA data, highlighting its capability to take designs within both the datasets. Notably, the BPDNN-ERP system frequently progresses its parameters in declining the alterations amongst the real and predictive TRA class labels.

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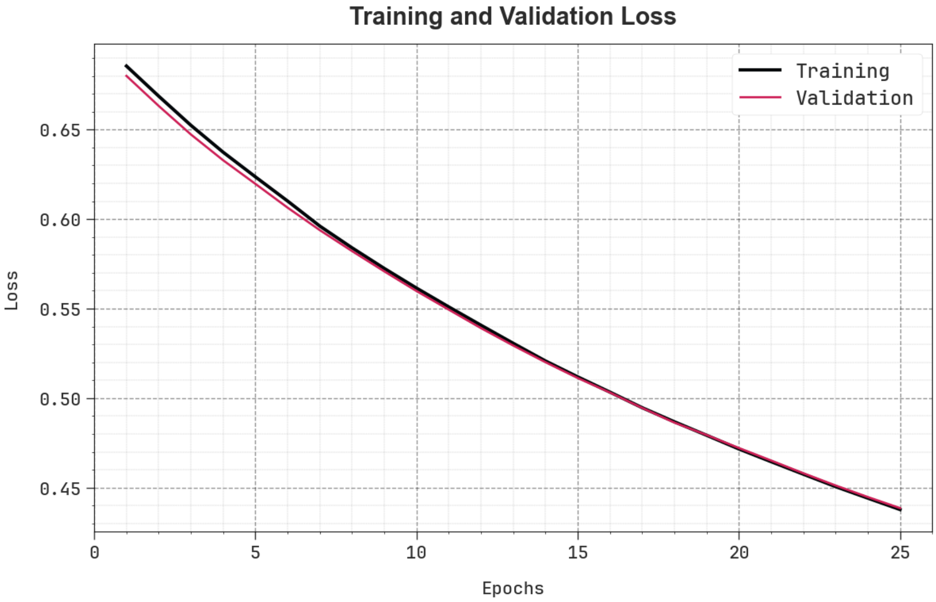

Figure 7: Loss curve of the BPDNN-ERP system

The performance of the BPDNN-ERP approach is equated with other approaches in Table 3 and Fig. 8 [20]. With respect to $accu_y$, the BPDNN-ERP system provides enhanced $accu_y$ of 91.59% whereas the NN, SVM, XGBoost, KNN, RF, and DT techniques get reduced $accu_y$ of 82.38%, 84.28%, 81.00%, 87.29%, 86.55%, and 83.40%, respectively. Likewise, based on $prec_n$, the BPDNN-ERP method offers enlarged $prec_n$ of 91.39% whereas the NN, SVM, XGBoost, KNN, RF, and DT systems get decreased $prec_n$ of 85.01%, 83.02%, 84.02%, 89.74%, 89.94%, and 84.62%, correspondingly. Lastly, based on $F1_{score}$, the BPDNN-ERP approach provides improved $F1_{score}$ of 91.41% while the NN, SVM, XGBoost, KNN, RF, and DT methods achieved decreased $F1_{score}$ of 82.01%, 83.01%, 83.01%, 84.65%, 87.55%, and 90.64%, correspondingly. Therefore, the BPDNN-ERP system can be used for improved outcomes.

Table 3: Comparative analysis of BPDNN-ERP model with recent algorithms

Method	$Accu_y$	$Prec_n$	$Reca_l$	$F1_{Score}$
Neural Net	82.38	85.01	79.02	82.01
SVM Model	84.28	83.02	83.01	83.01
XGBoost	81.00	84.02	81.01	83.01
KNN Algorithm	87.29	89.74	85.13	84.65
Random Forest	86.55	89.94	89.47	87.55
Decision Tree	83.40	84.62	82.55	90.64
BPDNN-ERP	91.59	91.39	91.59	91.41

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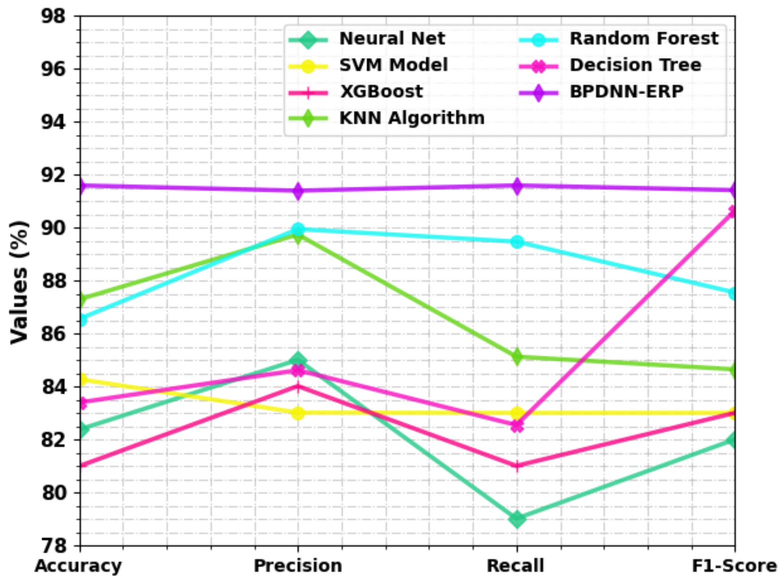

Figure 8: Comparative outcome of BPDNN-ERP system with recent algorithms

4. Conclusion

In this research work, we have presented a BPDNN-ERP method on the value of accounting information. The main objective of the BPDNN-ERP technique contains different kinds of processes involved as feature selection using HSA, DNN-based prediction, and MRFO-based parameter-tuning process. The BPDNN-ERP system begins with HSA for electing feature subsets. In addition, the BPDNN-ERP technique applies the DNN model for the prediction of bankruptcies. To enhance the performance of the DNN system, the MRFO technique can be used. The experimental study specified the enhanced performance of the BPDNN-ERP approach equated to existing forecasting approaches

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