An Innovative Approach to Financial Distress Prediction Using Relative Weighted Neutrosophic Valued Distances

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Abstract

The financial constraints of companies listed jeopardize the interests of employees and internal managers but also carries significant threats to outer investor and other stakeholders. Thus, there is need to create an effective financial distress predictive system. The two most pressing issues in finance are assessing credit risk and predicting bankruptcies. Thus, credit scoring and financial distress prediction remain crucial areas of research in the financial industry. Previous research has aimed at the design of ML and statistical approaches to predict the financial distress of the company. Neutrosophic set may be utilized, which is a generality of classical, fuzzy, and intuitionistic fuzzy sets (IFS). They establish a foundation for addressing inconsistency, indeterminacy, and uncertainty associated with real-world challenges. This study presents an Innovative Approach to Financial Distress Prediction using Relative Weighted Neutrosophic Valued Distances (IAFDP-RWNVD) technique. The IAFDP-RWNVD technique intends to estimate the occurrence of financial distress in any firm or organization. In the IAFDP-RWNVD technique, two major processes are comprised. At the primary stage, the IAFDP-RWNVD technique applies RWNVD technique for the identification of financial distress. In the second stage, the IAFDP-RWNVD technique designs fish swarm algorithm (FSA) for finetuning the RWNVD model. The experimental outcomes of the IAFDP-RWNVD method is investigated using distinct aspects. The experimentation outcome shows the improvements of the IAFDP-RWNVD technique.

Keywords: Intuitionistic Fuzzy Sets; Financial Distress Prediction; Neutrosophic Set; Fish Swarm Algorithm; Neutrosophic Valued Distance

1. Introduction

The powerful tool for modelling uncertainties in management issues are the neutrosophic set (NS) and its expansions are interval complex NS (ICNS), complex NS (CNS), and interval NS (INS) [1]. The effective tool for representing uncertainties and fuzziness in making decisions are the NS adds generality of the fuzzy set, traditional set, and IFSs including 3 ranks of falsehoods, truths, and indefiniteness of a complete report [2]. However, to adjust this NS to further actual difficult cases, CNS and INS are recommended consequently. Financial distress prediction (FDP) to much crucial in enterprise risk administration, particularly for financial organizations [3]. Particularly, financial organizations were to improve several risk administration methods likely credit scoring models and bankruptcy prediction [4].

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On account of bankruptcy predictions, financial organizations require active prediction techniques to create properly affording results. On the other side, the credit grading model is applied for managing major loan cases or else credit admittance calculation [5]. In particular, bankruptcy predictions and credit scores are the 2 binary categorization difficulties in financial trouble calculation, that are aimed at allocating a novel observation to two predefined conclusion programs (e.g., 'bad' and 'good' risks class).

In the following research, they too applied a collaborative method for FDP [6]. Numerous machine learning algorithms and ensemble methods are used in FDP for their best forecasting presentation in the work of literature, and then stakeholders proceed by attention in their acceptance of them [7]. Nowadays, several computer research workers have started to offer themselves to the descriptive researchers of ML techniques [8]. Furthermost explainable Artificial Intelligence (XAI) researchers are not for end operators, but for ML engineering scholars they make use of explanation methods to debug replicas. There is a huge gap between the aim of clarity, and explaining skill in preparation, as clarifications mainly help interior investors instead of exterior ones [9]. This research carries FDP as a functional positioned environment, examines which one of the exterior stakeholders is and whatever their interpretive requirements are, and then launches an understandable outline for FDP [10].

This study presents an Innovative Approach to Financial Distress Prediction using Relative Weighted Neutrosophic Valued Distances (IAFDP-RWNVD) technique. The IAFDP-RWNVD technique intends to estimate the occurrence of financial distress in any firm or organization. In the IAFDP-RWNVD technique, two major processes are comprised. At the primary stage, the IAFDP-RWNVD technique applies RWNVD technique for the identification of financial distress. In the second stage, the IAFDP-RWNVD technique designs fish swarm algorithm (FSA) for finetuning the RWNVD approach. The experimental outcomes of the IAFDP-RWNVD method is investigated using distinct aspects.

2. Related Works

Ayuni et al. [11] main goal is to enhance the efficiency of SVM method in forecasting the financial constraints of assets and construction business. The optimizer model employed is Particle Swarm Optimizer (PSO). PSO, which is the familiar model to enhance SVM features. The PSO technique acquires its signals from how a set of birds or insects upholds life. Set in a D-dimension search range, the PSO technique utilizes a particles that are measured as a random point. Chen et al. [12] proposed a new light space-SMOTE up sampling model that will decrease the feature dimension upsurge the signal-to-noise ratio (SNR) and then up sample it to enhance numerous minor class samples. Furthermore, this paper projected an effective ensemble framework (LiFoL) that unites focal loss (FL), light space-SMOTE, and LightGBM that can concentrate additional on minor classes and also get better performance.

In [13], developed a cost-sensitive learning model for the FDP. Now, a dual-stage FS model has been employed to pick the optimum feature set. A CSStacking ensemble technique has been proposed with nominated features in order to create a last forecast. The opposite T-test and non-parametric Wilcoxon test were utilized for checking the major variances among benchmark and CSStacking methods. In [14], an explainable AI technique such as complete procedure ensemble model and an explainable frame for FDP is here projected. At first, a dual-phase scheme combined with a wrapper and filter method is planned for feature selection. Next, manifold ensemble techniques are discovered and they are assessed as per the actual case. Lastly, the explanations of Shapley, partial additive and counterfactual dependence plots are used for enhancing the model interpretability.

Wang et al. [15] developed to prolong interpretable and graph contrastive learning ML in the background of a network, which is designed by different entities (persons and companies) and events (negative and positive), as well as utilizes the propagation effect in secure models for economic distress valuation of SME. At last, the method projects an original artifact by depicting social learning and homophily models. Ghosh and Dragan [16] help to dual granular hybrid predictive structures to find out the characteristic form of economic stress through numerous geography and variables. The proposed method were appealed on highest of the decomposed modules to fully examine the probability of last stress parameters controlled by the Office of Financial Research (OFR).

3. The Proposed Model

In this work, we design a new IAFDP-RWNVD method. The IAFDP-RWNVD system intends to estimate the occurrence of financial distress in any firm or organization. In the IAFDP-RWNVD technique, two major processes are comprised. Fig. 1 depicts the entire flow of IAFDP-RWNVD technique.

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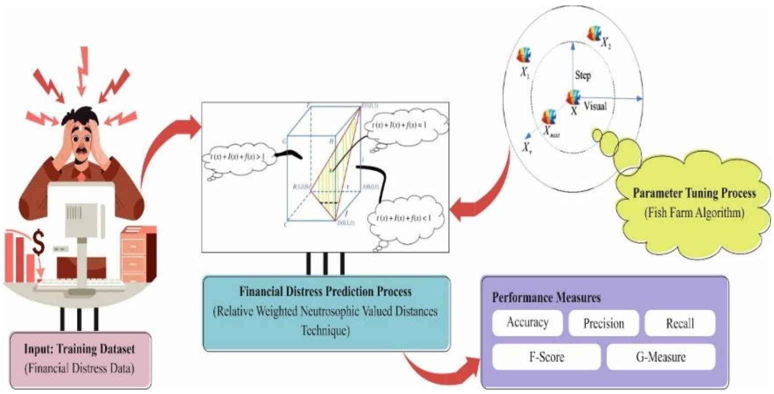

Figure 1. Overall flow of IAFDP-RWNVD technique

A. Predictive Modeling using RWNVD

At the primary stage, the IAFDP-RWNVD technique applies RWNVD technique for the identification of financial distress. Generally, the space has been evaluated through few operators that are definite in few sets of non-empty. In metric spaces, the operators contain 0 values based on value and set [17].

Description 8. Consider A as a non-empty SVNS and $x = \langle T_x, I_x, F_x \rangle, y = \langle T_y, I_y, F_y \rangle$ as a dual SVNN. The operations include multiplication and addition, with scalar$\alpha \in \mathbb{R}^+$, and exponential of SVNNs was definite below, correspondingly:

$$x \oplus y = \langle T_x + T_y - T_x T_y, I_x I_y, F_x F_y \rangle$$

$$x \odot y = \langle T_x T_y, I_x + I_y - I_x I_y, F_x + F_y - F_x F_y \rangle$$

$$\alpha x = \langle 1 - (1 - T_x)^\alpha, I_x^\alpha, F_x^\alpha \rangle$$

$$x^\alpha = \langle T_x^\alpha, 1 - (1 - I_x)^\alpha, 1 - (1 - F_x)^\alpha \rangle$$

From this description, we contain the subsequent theorems as an outcome:

Theorem1. Assume $x = \langle T_x, I_x, F_x \rangle$ as an SVNN. The impartial portion of the addition operators of sequence A is given as $0_A = \langle 0,1,1 \rangle$.

Assume $0_A = \langle T_0, I_0, F_0 \rangle$ and $x = \langle T_x, I_x, F_x \rangle$ as a dual SVNN and utilizing Description 8 we will get

$$x \oplus 0_A = \langle T_x + T_0 - T_x T_0, I_x I_0, F_x F_0 \rangle = \langle T_x, I_x, F_x \rangle$$

$$\Rightarrow \langle T_0, I_0, F_0 \rangle = \langle 0,1,1 \rangle = 0_A$$

To equate the neutrosophic value depending upon a neutral element, we will compute the functions of accuracy and score of an impartial component$0_A = \langle 0,1,1 \rangle$, correspondingly:

$s_0 = \frac{1 + T_0 - 2I_0 - F_0}{2} = -1$ and $h_0 = \frac{2 + T_0 - I_0 - F_0}{3} = 0$

Theorem2. Assume $x = \langle T_x, I_x, F_x \rangle$ as a SVNN. In multiplication operator, the neutral element of A is $1_A = \langle 1,0,0 \rangle$.

Proof. Assume $x = \langle T_x, I_x, F_x \rangle$ and $1_A = \langle T_1, I_1, F_1 \rangle$ as a dual SVNN and utilizing Definition8, we will get

$$x \odot 1_A = \langle T_x T_1, I_x + I_1 - I_x I_1, F_x + F_1 - F_x F_1 \rangle = \langle T_x, I_x, F_x \rangle$$

$$\Rightarrow \langle T_1, I_1, F_1 \rangle = \langle 1,0,0 \rangle = 1_A$$

Here, we examine the general metrics in the meaning of neutrosophic.

Description 9. Description 6 provides an order relationship for SVNN components. Assume that the mapping:$X \times X \to A$, whereas X and A denote the SVNS:

$0_A \leq d(x, y)$ and $d(x, y) = 0_A \Leftrightarrow s_x = s_y$ and $h_x = h_y$ for all $x, y \in X$.

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$d(x, y) = d(y, x)$ for all $x, y \in X$.

Here, d is denoted as neutrosophic value metric on X, and the set (X, d) was named neutrosophic value metric space. The 3rd state (triangular inequality) is not appropriate for SVNS because the addition is not normal.

Theorem3. Assume (X, d) as a neutrosophic value metric space. Next, the relations amongst the values of indeterminacy, falsity and truth:

(I) $0 < T(x, y) - 2I(x, y) - F(x, y) + 3$ and if $s_0 = s_d$ then $0 < T(x, y) - I(x, y) - F(x, y) + 2$.

(II) If $d(x, y) = 0_A \Leftrightarrow T(x, y) = 0, I(x, y) = F(x, y) = 1$.

(III) $T(x, y) = T(y, x), I(x, y) = I(y, x), F(x, y) = F(y, x)$ So, every function of distance should be symmetric. Whereas, $I(.,.)$, $F(.,.)$ and $T(.,.)$ represents the distance of the indeterminacy, falsity and truth, correspondingly.

Proof.

$$0_A < d(x, y) \Leftrightarrow \langle 0,1,1 \rangle < \langle T(x, y), I(x, y), F(x, y) \rangle$$

(I) $\Leftrightarrow s_0 < s_d \Leftrightarrow -1 < \frac{1+T(x,y)-2I(x,y)-F(x,y)}{2} \Leftrightarrow 0 < T(x, y) - 2I(x, y) - F(x, y) + 3$

(II) $d(x, y) = d(y, x) \Leftrightarrow \langle T(x, y), I(x, y), F(x, y) \rangle = \langle T(y, x), I(y, x), F(y, x) \rangle$

$$\Leftrightarrow T(x, y) = T(y, x), I(x, y) = I(y, x), F(x, y) = F(y, x)$$

Consider A as a non-empty SVNS and $x = \langle T_x, I_x, F_x \rangle, y = \langle T_y, I_y, F_y \rangle$ as a dual SVNN. If we describe the metric$d: X \times X \to A$, as:

$$d(x, y) = \langle T(x, y), I(x, y), F(x, y) \rangle = \langle |T_x - T_y|, 1 - |I_x - I_y|, 1 - |F_x - F_y| \rangle$$

then

$0 < |T_x - \tau_y| - 2(1 - |I_x - I_y|) - (1 - |F_x - F_y|) + 3 \Rightarrow 0 < |T_x - \tau_y| + 2|I_x - I_y| + |F_x - F_y|$. Then it fulfills the 1st state.

Due to the assets of the absolute values function, this state was clear. Therefore, (X, d) refers to a neutrosophic-value metric space.

Description 10. Assume that X and A a non-empty SVNS. A $G: X \times X \times X \to A$ is named neutrosophic value G-metric, if it fulfils the subsequent assets:

$G(x, y, z) = 0_A$ if and only if $x = y = z$,

$G(x, x, y) \neq 0_A$ when $x \neq y$,

$G(x, x, y) \leq G(x, y, z)$ for any $x, y, z \in X$, with $z \neq y$,

$G(x, y, z) = G(x, z, y) = \cdots$ (symmetric for every elements).

The set (X, G) is named a neutrosophic value G-metric space.

Theorem4. Assume that (X, G) as a neutrosophic value G-metrics, it fulfills the subsequent:

$$T(x, x, x) = 0, I(x, x, x) = F(x, x, x) = 1.$$

Let $x \neq y$, then $T(x, y, z) \neq 0, I(x, y, z) \neq 1, F(x, y, z) \neq 1$.

$$0 < T(x, y, z) - T(x, x, y) + 2(I(x, x, y) - I(x, y, z)) + F(x, x, y) - F(x, y, z)$$

$T(x, y, z), I(x, y, z)$ and $F(x, y, z)$ are symmetric for every element.

Here, $I(.,.)$, $T(.,.)$, and $F(.,.)$ denotes the G-distance function values of indeterminacy, truth, and falsity, correspondingly.

Proofs were prepared in the same method to neutrosophic value metric spaces.

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Instance 4. Assume that X is a non-empty SVNS and the G- function is expressed below:

$$G(x,y,z) = \frac{1}{3}\big(d(x,y) \oplus d(x,z) \oplus d(y,z)\big)$$

Whereas, $d(.,.)$ denotes a neutrosophic value metric. The set (X,G) is a neutrosophic value G-metric space due to $d(.,.)$. Additionally, it contains commutative properties.

The relative measure is nothing but a model, which is employed for grouping datasets.

Assume $x_j = \langle T_{x_j}, F_{x_j}, I_{x_j} \rangle \in A$ (non-empty SVNS), $i = 0 \dots n$ as a SVNN.

$$M_a(A) = \sum_{i=1}^{n} x_i x_i = \langle 1 - \prod_{i=1}^{n}(1 - T_{x_i})^{x_i}, \prod_{i=1}^{n}(I_{x_i})^{x_i}, \prod_{i=1}^{n}(F_{x_i})^{x_i} \rangle$$

Here, x_i denotes a weight for the i^{th} data. For a given dataset of neutrosophic $W = \{w_1, w_2, w_3, \dots, w_n\}$ and d represents a NS metrics. Here, an RNVD space is defined for picking further neutrosophic data of reference and calculate the RVND as the norm of spaces for each neutrosophic data $w_j \in W$.

Description 11. The RVND from neutrosophic data w_i to an additional neutrosophic data w_j was definite below:

$$RD\left(w_i \| w_j\right) = \frac{1}{n}\sum_{w_k \in W}\left(d(w_i, w_j) \ominus d(w_i, w_k)\right)$$

Here, the values of T, I, F are not negative, so we describe $d(w_i, w_j) \ominus d(w_i, w_k)$ as the distance among dual neutrosophic value metrics. The related neutrosophic-value distance is expressed below:

$$d(w_i,w_i) \ominus d(w_i,w_k) = \langle T(w_i,w_i), I(w_i,w_i), F(w_i,w_i)\rangle \ominus \langle T(w_i,w_k), I(w_i,w_k), F(w_i,w_k)\rangle$$
$$= \langle 1 - |T(w_i, w_i) - (T(w_i, w_k) - 1)^2|, 1 - |I(w_i, w_i) - I(w_i, w_k)^2|,$$
$$1 - |F(w_i,w_i) - F(w_i,w_k)^2|\rangle \quad (1)$$

The operator of difference $\ominus$ usually is not a metric of neutrosophic-valued.

$RD(w_i \| w_j) = \frac{1}{n}\sum_{w_k \in W}(d(w_i, w_j) \ominus d(w_i, w_k))$

$$= d(w_i,w_j) \ominus \frac{1}{n}\sum_{w_k \in W} d(w_i,w_k)$$

$$= \langle T(w_i, w_j), I(w_i, w_j), F(w_i, w_j)\rangle \ominus \frac{1}{n}(d(w_i, w_1) \oplus d(w_i, w_2) \oplus \dots \oplus d(w_i, w_n))$$

$$= \langle T(w_i, w_j), I(w_i, w_j), F(w_i, w_j)\rangle$$

$$\ominus \frac{1}{n}[\langle T(w_i,w_1), I(w_i,w_1), F(w_i, w_1)\rangle \oplus \dots \oplus \langle T(w_i,w_1), I(w_i,w_1), F(w_i, w)]$$

$$= \langle T(w_i, w_j), I(w_i, w_j), F(w_i, w_j)\rangle$$

$$\ominus \frac{1}{n}\left[\langle \sum_{k \in W} T(w_i, w_k) - \prod_{k \in W} T(w_i,w_k), \prod_{k \in W} I(w_i,w_k), \prod_{k \in W} F(w_i,w_k)^{1/n}\rangle\right]$$

$$= \langle T(w_i, w_j), I(w_i, w_j), F(w_i, w_j)\rangle$$

$$\ominus \langle 1 - \left[1 - \sum_{k \in W} T(w_i, w_k) + \prod_{k \in W} T(w_i,w_k)\right]^{\frac{1}{n}}, \left[\prod_{k \in W} I(w_i, w_k)\right]^{1/n}, \prod_{k \in W} F(w_j, w_k)^{1/n}\rangle$$

$$= \langle T_1, I_1, F_1\rangle \ominus \langle T_2, I_2, F_2\rangle$$

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$$= \langle 1 - |T_1 - (T_2 - 1)^2|, 1 - |I_1 - I_2{}^2|, 1 - |F_1 - F_2^2| \rangle$$

Here, T_1, I_1, F_1 and T_2, I_2, F_2 denotes the two components of SVNN, correspondingly.

Description 12. The RWNVD w_i to w_j was definite below:

$$RD_\chi(w_i) = \sum_{w_i \in W} \chi_i \, RD_x(w_i \| w_j)$$

$$= \sum_{w_i \in W} \chi_i \left[\sum_{w_i \in W} \chi_w \big(d(w_i, w_j) \ominus d(w_i, w_k) \big) \right]$$

$$= \sum_{w_i \in W} \chi_i \left[\sum_{w_i \in W} \chi_w \big(\delta(d_{ij}, d_{ik}) \big) \right]$$

Definition 13. The RWNVD from a neutrosophic dataset W_1 to another neutrosophic dataset W_2 is definite below:

$$RD_\chi(W_1 \| W_2) = \sum_{x \in W_1} \chi_x \sum_{y \in W_2} \chi_y \, RD_\chi(x \| y)$$

$$\rho_\chi(w_{j,} w_j) = RD_\chi(w_j) \ominus RD_\chi(w_i \| w_j) \quad (2)$$

The weighted neutrosophic-value metrics among dual datasets of neutrosophic w_i and w_j. If $\rho_\chi(w_i, w_j) \geq 0_W$ (resp. $\rho_\chi(w_i, w_j) \leq 0_W$), then w_i and w_j we're supposed to be cohesive.

Definition 14. (Weighted cohesion measure among dual datasets of neutrosophic) Assume that w_i and w_j as elements of neutrosophic datasets U and V, correspondingly. Then, it is expressed below,

$$\rho_\chi(U, V) = \sum_{w_i \in U} \chi_u \sum_{w_i \in V} \chi_v \, \rho_\chi\big(w_{i'} w_j\big) \quad (3)$$

The equation is named as the measure of weighted cohesion neutrosophic-value of the neutrosophic datasets U and V

Description 15. (Cluster): If it is unified, then the non-empty neutrosophic dataset W was termed as a cluster. That is $\rho(W, W) \geq 0_W$.

B. Model Fine-tuning

In the second stage, the IAFDP-RWNVD technique designs FSA for fine-tuning the RWNVD approach. FSA is stimulated by the foraging behavior of fish [18]. When fishes are searching for food, they usually the behavior of collecting, following and swimming. As per these behaviours, the FSA gets 3 optimizer behaviours such as foraging, following and clustering.

Furthermore, there is a herding factor δ. Individuals can estimate the fish density and food at the target position over inequality $\frac{Y}{nf} \geq \delta Y_i$, to define whether rear end behavior and group behavior arise.

Here, Y represents the fitness value of target, nf refers to the numeral of other individuals in present individual, Y_i and signifies the fitness value of present individual.

The complete details of every behavior are explained below.

1) CLUSTERING BEHAVIOR

In this behavior, the individual shifts to the focus point of every individual within the area of vision. The formulation is presented in Eqs. (4) and (5).

$$X_i^{t+1} = X_i^t + \frac{X_c - X_i^t}{|X_c - X_i^t|} rand(0,1) \times step \; if \; Y_i^{t+1} > Y_i^t and Y_c / nf \geq \delta Y_i \quad (4)$$

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$$X_c = \left(\sum_{j=1}^{nf} X_j\right)/nf \tag{5}$$

Whereas, X_i^t denotes the i^{th} individual in the t^{th} iteration is the present individual, and X_c refers to the focus point within the visual of X_i, X_j signifies the j^{th} individual in present individual visual, nf is the numeral of other individuals in the present individual visual.

2) FOLLOWING BEHAVIOR

In this, the present individual travels to the optimum individual within the visual. The mathematical equation of this behavior is given below:

$$X_i^{t+1} = X_i^t + \frac{X_b - X_i^t}{|X_b - X_i^t|}\, rand\ (0,1) \times stepif\ Y_i^{t+1} > Y_i^t\ and\ Y_b/nf \geq \delta Y_i \tag{6}$$

Here, X_b signify the individuals with the finest fitness values in the visual of present fish X_i^t.

3) FORAGING BEHAVIOR

FSA executes foraging behavior when neither clustering nor tail-chasing behavior is executed. FSA mostly trusts on foraging behavior to get more populace diversity and discover better areas. When the behavior of foraging cannot able to find a better location after number of $t\eta_{-}$number, the individual will arbitrarily get a location in visual to transfer. The numerical calculations are exposed in Eqs. (7) and (8).

$$X_i^{t+1} = X_i^t + \frac{X_r - X_i^t}{|X_r - X_i^t|} rand(0,1) \times step\ if Y_i^{t+1} > Y_i^t \tag{7}$$

$$X_i^{t+1} = X_i^t + rand(-1,1) \times step \tag{8}$$

Here, X_i denotes the present individual and X_r is a randomly generated location within the visual of X_i. Fig. 2 illustrates the flowchart of FSA.

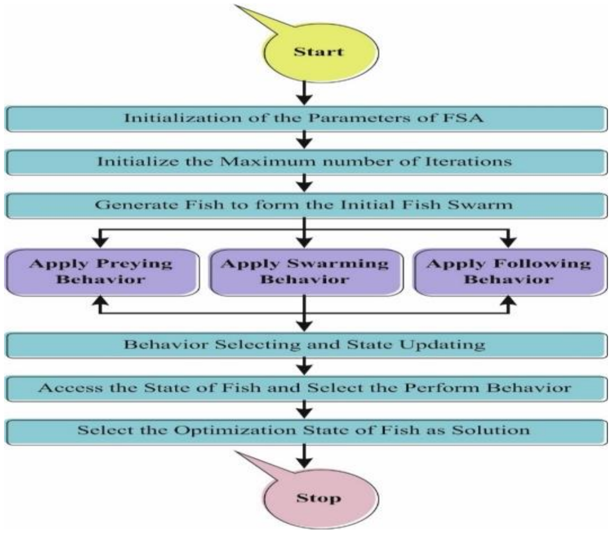

Figure 2. Flowchart of FSA

Thus, the below mentioned are some of the basic steps of FSA algorithm.

Step1: Set the population and give the optimum individual to the bulletin board.

Step2: Considering the behavior that an individual desires to perform.

Step3: Upgrade bulletin boards and fish swarm.

Step4: If the output conditions are got, output the bulletin board, or else go to step 2.

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The FSA improves an FF to achieve upgraded classifier outcomes. It defines a positive integer to epitomize the superior accuracy of the candidate results. Now, the decay of the classifier error rate is taken as the FF, as follows.

$$fitness(x_i) = ClassifierErrorRate(x_i)$$

$$= \frac{No\ of\ misclassified\ samples}{Total\ No.of\ samples} * 100 \quad (9)$$

4. Result Analysis and Discussion

The experimental validation of the IAFDP-RWNVD method is tested using Australian credit and Analact dataset [19] as shown in Table 1.

Table 1: Details of two datasets

Dataset	Source	instances	attributes	# of class	Bankrupt/Non-Bankrupt
Australian	UCI	690	14	2	383/307
Analcat	stern	50	5	2	25/25

The results of the IAFDP-RWNVD technique on the Australian dataset are displayed in Table 2 and Fig. 3. The outcomes imply that the IAFDP-RWNVD method properly recognizes the samples. On 70%TRP, the IAFDP-RWNVD technique provides average $accu_y$ of 97.72%, $prec_n$ of 97.91%, $reca_l$ of 97.67%, F_{score} of 97.67%, and $G_{measure}$ of 97.68%. Additionally, on 30%TSP, the IAFDP-RWNVD method delivers average $accu_y$ of 99.03%, $prec_n$ of 99.09%, $reca_l$ of 98.99%, F_{score} of 99.03%, and $G_{measure}$ of 99.04%.

Table 2: Classifier outcomes of IAFDP-RWNVD technique on Australian dataset

Australian Dataset					
Class	$Accu_y$	$Prec_n$	$Reca_l$	F_{Score}	$G_{Measure}$
TRP (70%)					
Bankrupt	97.72	96.81	99.27	98.03	98.03
Non-Bankrupt	97.72	99.00	95.67	97.31	97.32
Average	97.72	97.91	97.47	97.67	97.68
TSP (30%)					
Bankrupt	99.03	98.18	100.00	99.08	99.09
Non-Bankrupt	99.03	100.00	97.98	98.98	98.98
Average	99.03	99.09	98.99	99.03	99.04

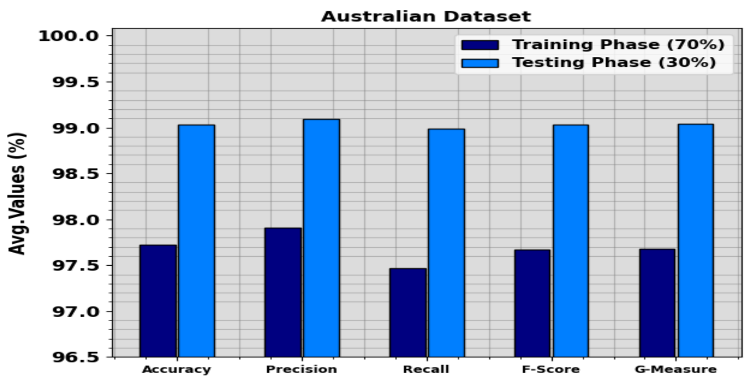

Figure 3. Average outcome of IAFDP-RWNVD technique on Australian dataset

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In Fig. 4, the PR study of the IAFDP-RWNVD method offers understanding of its presentation by scheming Precision against Recall for each class label. The figure displays that the IAFDP-RWNVD model always achieves amended PR values across diverse classes, demonstrating its capability to preserve a substantial percentage of true positive predictions amongst positive predictions (precision) while also taking a great quantity of real positives (recall). The steady intensification in PR outcomes among each class depicts the efficiency of the IAFDP-RWNVD method in the classifier model.

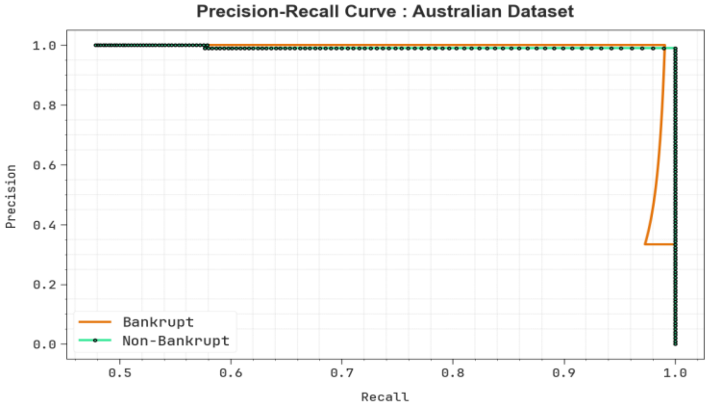

Figure 4. PR curve of IAFDP-RWNVD technique on Australian dataset

Table 3 and Fig. 5 report the comparison investigation of the IAFDP-RWNVD technique on the Australian dataset [20]. The results highlighted that the LR and RBFNetwork models have shown the lowest performance. At the same time, the TLBO-Deep, Deep NN, and OD-PODNN models have obtained closer results. Nevertheless, the IAFDP-RWNVD technique demonstrates superior results with improved $prec_n$ of 99.09%, $reca_l$ of 98.99%, $accu_y$ of 99.03%, and F_{score} of 99.03%.

Table 3: Comparative analysis of IAFDP-RWNVD technique with existing models on Australian dataset

Australian Dataset				
Methods	$Prec_n$	$Reca_l$	$Accu_y$	F_{Score}
IAFDP-RWNVD	99.09	98.99	99.03	99.03
OD-PODNN	98.98	96.43	97.65	96.09
TLBO-Deep	96.20	90.29	94.05	93.15
DNN	92.43	87.62	91.34	89.96
LR	65.79	85.23	79.71	74.26
RBF Network	86.31	81.53	85.21	83.86

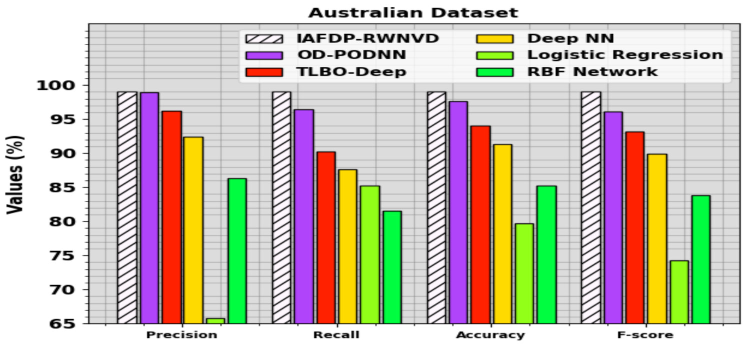

Figure 5. Comparative analysis of IAFDP-RWNVD method on Australian dataset

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The outcomes of the IAFDP-RWNVD method on the Analcat dataset are described in Table 4 and Fig. 6. The outcomes suggest that the IAFDP-RWNVD system accurately identifies the samples. On 70%TRP, the IAFDP-RWNVD method offers average $accu_y$ of 97.14%, $prec_n$ of 97.62%, $reca_l$ of 96.67%, F_{score} of 97.06%, and $G_{measure}$ of 97.10%. Furthermore, on 30%TSP, the IAFDP-RWNVD method delivers average $accu_y$ of 93.33%, $prec_n$ of 91.67%, $reca_l$ of 95.00%, F_{score} of 92.82%, and $G_{measure}$ of 93.08%.

Table 4: Classifier outcome of IAFDP-RWNVD technique on Analcat dataset

Analcat Dataset					
Class	$Accu_y$	$Prec_n$	$Reca_l$	F_{Score}	$G_{Measure}$
TRP (70%)					
Bankrupt	97.14	100.00	93.33	96.55	96.61
Non-Bankrupt	97.14	95.24	100.00	97.56	97.59
Average	97.14	97.62	96.67	97.06	97.10
TSP (30%)					
Bankrupt	93.33	100.00	90.00	94.74	94.87
Non-Bankrupt	93.33	83.33	100.00	90.91	91.29
Average	93.33	91.67	95.00	92.82	93.08

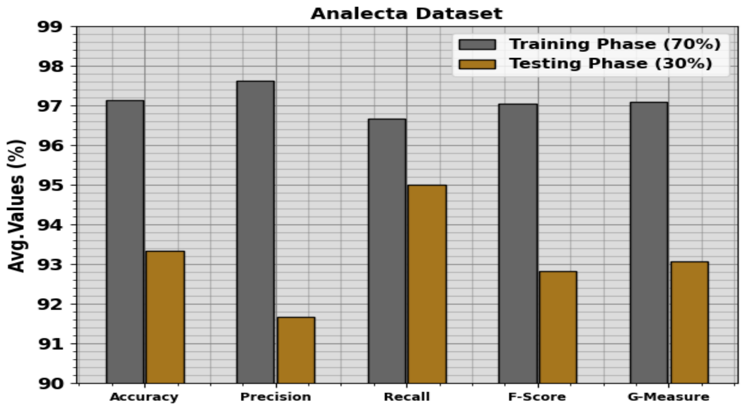

Figure 6. Average outcome of IAFDP-RWNVD technique on Analact dataset

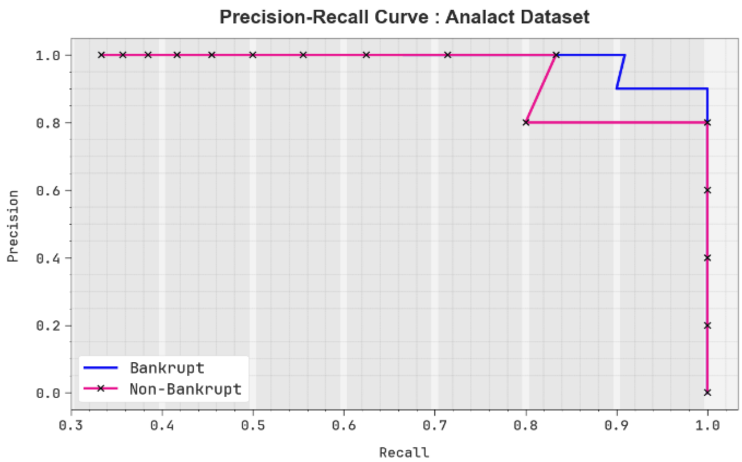

Figure 7. PR curve of IAFDP-RWNVD technique on Analact dataset

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In Fig. 7, the PR study of the IAFDP-RWNVD system explains its performance by scheming Precision against Recall for each class label. The figure displays that the IAFDP-RWNVD method always achieves upgraded PR values across dissimilar classes, representing its capability to preserve a substantial percentage of true positive predictions amongst each positive prediction (precision) while taking a great amount of real positives (recall). The steady rise in PR outcomes among each class depicts the efficiency of the IAFDP-RWNVD method in the classifier process.

Table 5 and Fig. 8 report the comparison investigation of the IAFDP-RWNVD approach on the Analact dataset. The outcomes emphasized that the LR and RBFNetwork methods have presented minimum performance. Simultaneously, the TLBO-Deep, Deep NN, and OD-PODNN methods have attained closer outcomes. Nonetheless, the IAFDP-RWNVD method establishes higher outcomes with enriched $prec_n$ of 97.62%, $reca_l$ of 96.67%, $accu_y$ of 97.14%, and F_{score} of 97.06%.

Table 5: Comparative analysis of IAFDP-RWNVD method with existing methods on Analcat dataset

Analcat Dataset				
Methods	$Prec_n$	$Reca_l$	$Accu_y$	F_{Score}
IAFDP-RWNVD	97.62	96.67	97.14	97.06
OD-PODNN	96.71	95.95	96.12	96.61
TLBO-Deep	95.99	92.30	96.00	96.00
Deep NN	96.00	85.00	90.00	90.56
LR	92.00	85.18	88.00	88.46
RBF Network	80.00	71.42	74.00	75.47

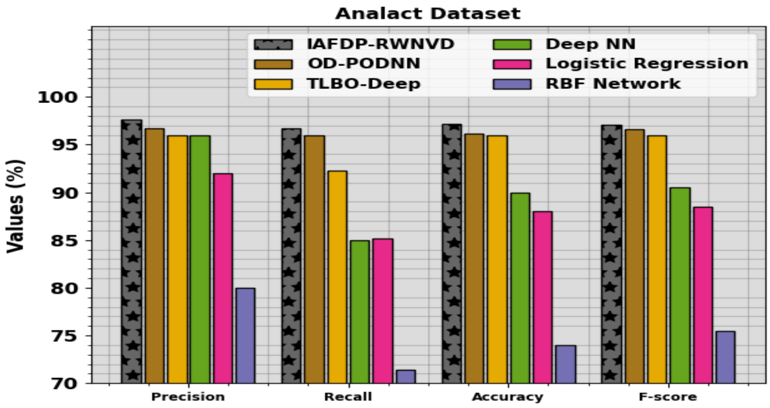

Figure 8. Comparative study of IAFDP-RWNVD technique on Analcat dataset

Thus, the IAFDP-RWNVD technique can be applied for enhanced detection of financial distress.

5. Conclusion

In this study, we design a novel IAFDP-RWNVD algorithm. The IAFDP-RWNVD technique intends to estimate the occurrence of financial distress in any firms or organization. In the IAFDP-RWNVD technique, two major processes are comprised. At the primary stage, the IAFDP-RWNVD technique applies RWNVD technique for the identification of financial distress. In the second stage, the IAFDP-RWNVD technique designs FSA for finetuning the RWNVD algorithm. The experimental outcomes of the IAFDP-RWNVD method is investigated using distinct aspects. The experimentation outcomes outlined the improvements of the IAFDP-RWNVD technique.

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