



Predictive Modeling of Financial Crisis Using Advanced Classification Models Powered by Neutrosophic Fusion of Rough Set Theory

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Abstract

Neutrosophic set (NS) and logic are powerful mathematical approaches for managing different uncertainties. Amongst different approaches for examining NS statistics, rough set theory (RST) offers a valuable instrument in the domain of NS statistics, and masses of researchers have been motivated by NS combination of RST. Recently, there have been no wide-ranging statistics and literature reviews of the universal RST and its applications. The Financial Crisis Prediction mechanism leverages cutting-edge computation methods to predict possible disruptions or economic downturns. By investigating past fiscal information, marketplace gauges, and macroeconomic features, the typical recognizes primary caution indications of imminent disasters. This practical method helps financial institutions, policymakers, and investors in applying pre-emptive procedures to alleviate fiscal marketplaces and threats. In this paper, we develop a Financial Crisis Prediction Model using Neutrosophic Fusion of Rough Set Theory (FCPM-NFRST) methodology. The suggested FCPM-NFRST method for financial crises incorporates numerous forward-thinking systems to improve predictive performance. It is initiated by the Firefly Algorithm (FFA) based feature selection to detect the fittest fiscal gauges. Consequently, the Neutrosophic Fusion of RST (NFRST) is exploited for strong cataloguing and successful management of vagueness and roughness in economic information. Lastly, the Whale Optimization Algorithm (WOA) is exploited for parameter fine-tuning, enhancing the system's accuracy. Investigational study displays that the FCPM-NFRST ensemble mechanism is more robust and superior than its complements. Accordingly, this study powerfully suggests that the suggested FCPM-NFRST method is very competitive than conventional and other existing algorithms.

Keywords: Financial Crisis Prediction; Rough Set Theory; Neutrosophic Set; Whale Optimization Algorithm; Feature Selection; Neutrosophic Fusion

1. Introduction

The theory of rough set (RS), is an official device for modelling and processing partial data in information schemes. Generally, two major elements in the RS concept are equivalence relation and crisp set, which establish the arithmetical base of RSs [1]. The fundamental ideas of an RS depend upon the estimation of a couple sets as an upper approximation and the lower estimate of sets [2]. Several ideas associated with the vague set, RS, intuitionistic fuzzy sets (IFS), and FS, are inserted including fuzzy rough sets, RFS, IFRS, generalized fuzzy rough, rough vague sets, and rough IFS [3]. The most interesting generalization of the notion of IFS and FS are the ideas of neutron-sophistic sets presented by F.Smarandache. Neutrosophic sets are described via 3 tasks: a non-membership function, a membership function, and an indeterminacy function which are all separately related to one another [4].

The most substantial area that helps financial institutes make conclusions at suitable moments for maintainable development objectives is financial crisis prediction (FCP) [5]. This is because of the purpose of improper decision-making in companies, leading to bankruptcy or financial emergency and upset vendors, investors, clients, etc., the present growth in information technology permits achieving various forms of information related to the risk stages of corporations from diverse manners [6]. Most of the public depends on the analyst's decision to assess a huge amount of information. On the other hand, copious factors may influence the analysis of the presentation. AI and arithmetical methods are used to detect FCP. Here, AI is applied in numerous methods [7]. AI is utilized to form replicas that forecast if a financial organization might suffer a difficulty. Most importantly, the big-data training models cannot only resolve the issue of the appropriateness of predicting then also maintain the link between ancient time sequences (financial data) and present financial pointers, to get additional exact financial crisis predicting outcomes [8]. Most of the scholars have completed in-depth studies on crisis predictions through ML techniques, to obtain accurate financial crisis forecast models.

With the advancement of deep learning (DL) technologies, very few researchers applied DL techniques to financial crisis forecasts and obtained better presentation on test datasets than standard neural networks [9]. Despite that, the benefits of these technologies have not been completely examined by earlier models and methods. Amongst the present depth methods, the recurrent neural network (RNN) models depending on LSTM are well suited to process financial-related information because they can efficiently use the long-distance reliant information in sequential data [10].

This paper develops a Financial Crisis Prediction Model using Neutrosophic Fusion of Rough Set Theory (FCPM-NFRST) methodology. The suggested FCPM-NFRST method for financial crises incorporates numerous forward-thinking systems to improve predictive performance. Primarily, the Firefly Algorithm (FFA) based feature selection to detect the fittest fiscal gauges. Consequently, the Neutrosophic Fusion of RST (NFRST) is exploited for strong cataloguing and successful management of vagueness and roughness in economic information. Lastly, the Whale Optimization Algorithm (WOA) is exploited for parameter fine-tuning, enhancing the system's accuracy. Investigational study displays that the FCPM-NFRST ensemble mechanism is more robust and superior than its complements.

2. Related Works

Liu et al. [11] presented a two-level methodology, manipulating CNN models for extracting features from financial pointers by using a LSTM approach from a consideration tool to capture the basic semantics in financial texts. Consequently, these models combined to extract features from both the source for powerful classifications. Ni and Xu [12] propose a deep learning (DL) technique for the investigation of stock market correlations. The mixed DCDNN method is established and derived from the Recurrent Deep Neural Network (RDNN) with DCC-GARCH techniques. DL was then planned for predicting the prediction errors of the DCC-GARCH models for increasing the estimation accuracy of stock market correlations. The auto-encoder was also presented in the experimental study for extracting valuable features of the stock directory information.

Li and Chen [13] developed a financial crisis initial cautionary method based on improving the fruit fly optimization algorithms-backpropagation neural networks (IFOA-BP). Initially, this technique selected itemized companies in the manufacturing industries as the investigation objects and used quantum computing for selecting financial crisis pointers. Then, this model proposed the IFOA, and it introduced orthogonal trial arrays in the initiating stage of the populations. Lastly, the IFOA is applied for the optimization of the BP neural network weights and certain limits of improving the model's forecasting presentation. Venkateswarlu et al. [14] designed the opposing Ant Lion Optimizer-based feature selection with the ML-enabling classifications (OALOFS-MLC) method for FCP in big-data surroundings. Additionally, the suggested OALOFS-MLC techniques designed unique OALOFS algorithms to select the best sub-set of features that aid in achieving enhanced categorization outputs. Moreover, the Deep Random Vector Functional Linked Networks (DRVFLN) approach is applied to performing the ranking processes.

In [15], a novel white shark optimization along with deep learning-based Bankruptcy Prediction for Financial Risk Assessments (WSODL-BPFCA) methods is presented. The introduced WSODL-BPFCA method uses a hyper-parameter-adjusted DL approach to predicting the presence of bankruptcy. To achieve this, the WSODL-BPFCA model uses min-max normalizations to change the incoming data into a uniform arrangement. For bankruptcy calculation, the WSODL-BPFCA techniques introduce an attention-based LSTM (ALSTM) method. Finally, the hyper-parameter fine-tuning of the models is performed to employ the WSO techniques. Mao et al. [16] recommended the Merton-LSTM approach, a varied LSTM algorithm designed by incorporating the Merton determinatives models, to predict the CDS indexes. This method provides the hard maths behind the Merton-

LSTM models; it shows that to leverage the nonlinear training capability of LSTM by increasing model ability, the Merton-LSTM method is estimated to learn the intrinsic connection between the CDS spreading and Merton elements.

3. The Proposed Model

In this paper, we have developed a new FCPM-NFRST methodology. The suggested FCPM-NFRST method for financial crises incorporates numerous forward-thinking systems to improve predictive performance. Figure 1 depicts the entire procedure of FCPM-NFRST methodology.

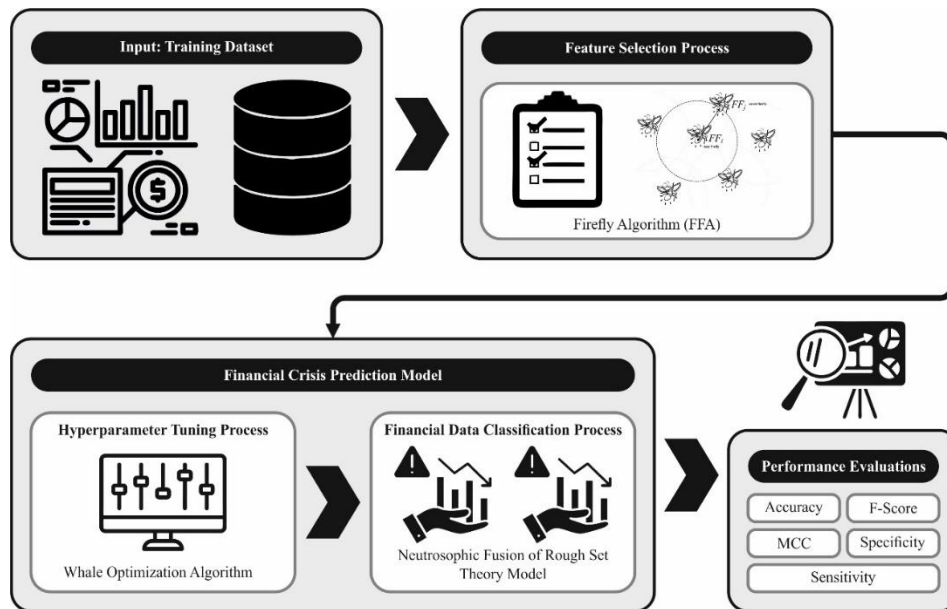


Figure 1. Overall process of FCPM-NFRST methodology

A. Feature Selection Process

Primarily, the FFA-based feature selection to detect the fittest fiscal gauges. FFA is a heuristic optimization approach for resolving the problems of optimization algorithms [17]. The algorithm operates on the flashing behaviour of FF. The concept behind is that it has some organic compounds known as luciferin. FF reacts with the luciferin and discharges light whenever the air enters the abdomen. This is a chemical compound, which discharges the light. The FA has been derived based on the flashing behavior and with the subsequent assumptions.

1. All fireflies are unisexual; others attract them.
2. The brightness describes the degree of attractiveness. The distance and brightness are directly proportional to one another. The FF are attracted by each other, which has more brightness, which means a nearby firefly.
3. If FF does not have more brightness than others do, in the search range they will move randomly.

Using FA, two factors are defined namely attractiveness and the light intensity variation. Attractiveness is defined by the fitness value measurement of the FF brightness.

$$I(r) = I_0 e^{-\gamma r} \quad (1)$$

Where $I(r)$ denotes the light intensity at distance r . γ indicates the light absorption coefficient.

$$\beta = \beta_0 e^{-\gamma r^2} \quad (2)$$

In Eq. (8), β_0 the attractiveness at the distance $r = 0$. Euclidean Distance is determined by the distance between two FFs. The search space has 'n' number of FF. Each FF participates in the optimization problem. At times, the i^{th} FFs are attracted by j^{th} FF and the distance is measured by,

$$r_{ij} = |s_i - s_j| \quad (3)$$

r_{ij} =distance between the i^{th} and j^{th} FFs.

The i th firefly moves randomly to the firefly. s_j Which has more brightness. This search process is done by random selection at particular time intervals. From this time it achieves the maximum no of iterations, and the best solution will be obtained by the objective function whether maximum or minimum.

$$s_i = s_i + \beta_0 e^{-\gamma r_{ij}^2} (s_j - s_i) + \alpha \varepsilon_i \quad (4)$$

Where α denotes the randomized parameter and ε_i denotes the random number. Steps included in the FFA algorithm are shown in Figure 2,

Step 1: Generation of initial population.

Step2: Assessment of fitness for the FFs from the objective function.

Step3: Update the fitness value.

Step4: Rank and update the firefly and its location.

Step5: Check for maximal iteration count.

Step6: Optimum outcome for the objective function.

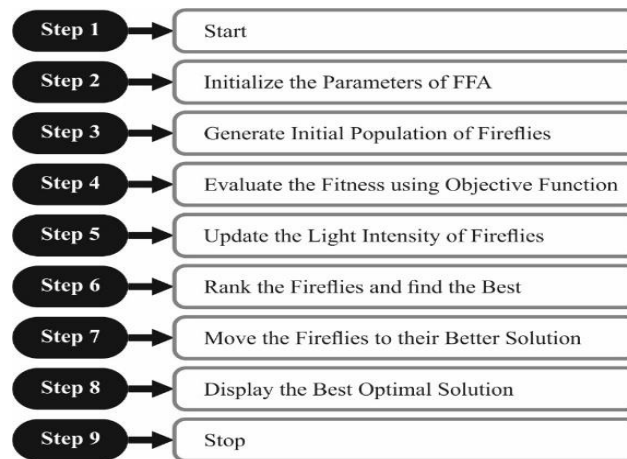


Figure 2. Steps involved in FFA

The FF consider the cataloguing accurateness and the quantity of features designated. It exploits the organization correctness and diminishes the size of the features designated. Hence, the FF evaluates discrete solution, as follows:

$$Fitness = \alpha * ErrorRate + (1 - \alpha) * \frac{\#SF}{\#All_F} \quad (5)$$

Here, *ErrorRate* is the classifier error rate and considered as the proportion of improper secret to the amount of organizations completed, in [0,1]. *#SF* demonstrates the quantity of features designated and *#All_F* shows the overall number of attributes in the original dataset. α controls the prominence of classifier quality and subset length.

B. FCP using NFRST Classifier

Afterwards, the NFRST is exploited for strong cataloguing, successfully managing vagueness and roughness in economic information. Smarandache introduced the NS conception based on the philosophical paradigm perspective that splits all the notions from the specific truth, indeterminacy and falsity degrees concurrently [18]. Later, NS established strong basics for a sequence of new scientific philosophies together with NSs, NSL, NS statistics, NS probability, and so on. Particularly, as a longer variation of traditional FL that focuses on realizing fundamental concept of NS, NL is a logic where all the propositions are evaluated to individual membership function of truth in a subsection μ , the indeterminate amount in a subsection ν , and the false degree in the subset

ω . Furthermore, NL offers the architecture of NS connections like disjunction, negation and conjunction that is paramount in NL combination of RST. The scientific formula of NS connection is given below.

In NL, Smarandache established NSs through non-regular investigation. In non-regular examination, a teeny value is described by the infinite smaller values. Assume ε refers to a teeny value, and the hyperactive-real value is a generality of the factual value that has class of infinitesimal and infinite numbers. Next, $1^+ = 1 + \varepsilon$ and $0^- = 0 - \varepsilon$ are two non-typical predetermined values, where “1” and “0” are average amounts, and “ ε ” is a non-normal amount. Clearly, 1^+ is superior to 1 and 0^- is lesser than 0.

Assume U as a random universal dissertation. For an overall constituent x in U , an NS A in U is in scientific terms given below:

$$A = \{(x, \mu_A(x), v_A(x), \omega_A(x)) | x \in U\}, \quad (6)$$

In Eq. (6), $\mu_A(x)$, $v_A(x)$ and $\omega_A(x)$ denotes the real normal or non-normal sets of the non-normal range $[0^-, 1^+]$, viz., $\mu, v, \omega: U \rightarrow]0^-, 1^+[$ characterizes the truth, the indeterminate and the false degrees correspondingly for all the components $x \in U$ to A . Therefore, an NS is created from philosophical viewpoints that make it challenging to overcome real-time situations. Furthermore, there is no certain constraint for $\mu_A(x) + v_A(x) + \omega_A(x)$. Thus, $0^- \leq \mu_A(x) + v_A(x) + \omega_A(x) \leq 3^+$.

In the NSs, it is challenging to directly exploit NSs in real-world applications owing to the interval of $\mu_A(x)$, $v_A(x)$ and $\omega_A(x)$ is constrained within $]0^-, 1^+[$. Rather than $]0^-, 1^+[$, it is essential to upgrade to $[0, 1]$. Therefore, the idea of SVNS is consequently proposed with the operator $\mu, v, \omega: U \rightarrow [0, 1]$ for all the components $\chi \in U$ to an SVNS H . Therefore $0 \leq \mu_H(x) + v_H(x) + \omega_H(x) \leq 3$. Furthermore, range value outperforms crisp value while handling imperfect data system, so it is normal to suggest the INS concept. For INS E , the operator $\mu, v, \omega: U \rightarrow \text{int}[0, 1]$ hold for all the components $x \in U$ to E , where range $[0, 1]$ is the closed range of $[0, 1]$. If $0 \leq \sup \mu_E(x) + \sup v_E(x) + \sup \omega_E(x) \leq 3$ is correct, where $\mu_E(x) = [\inf \mu_E(x), \sup \mu_E(x)]$, $v_E(x) = [\inf v_E(x), \sup v_E(x)]$ and $\omega_E(x) = [\inf \omega_E(x), \sup \omega_E(x)]$.

Regarding definite NS application, it is important to propose the mathematical formula of NS connection.

Assume U as a random universal discourse, A and A^f are two NSs as follows:

(1) Accompaniment: the accompaniment of A is

$$A^c = \{(x, \omega_A(x), 1 - v_A(x), \mu_A(x)) | x \in U\}. \quad (7)$$

(2) Connection: the connection of A and A' is

$$A \cap A' = \{(x, \min(\mu_A(x), \mu'_A(x)), \max(v_A(x), v'_A(x)), \max(\omega_A(x), \omega'_A(x))) | x \in U\}: \quad (8)$$

(3) Unification: the unification of A and A' is

$$A \cup A' = \{(x, \max(\mu_A(x), \mu'_A(x)), \min(v_A(x), v'_A(x)), \min(\omega_A(x), \omega'_A(x))) | x \in U\}: \quad (9)$$

(4) Addition: for x in U , $A \subseteq A^f$ has $\mu_A(x) \leq \mu'_A(x)$, $v_A(x) \geq v'_A(x)$ and $\omega_A(x) \geq \omega'_A(x)$:

(5) equality: for x in U , $A = A'$ has $\mu_A(x) = \mu'_A(x)$, $v_A(x) = v'_A(x)$ and $\omega_A(x) = \omega'_A(x)$.

Before the rough guide of original RSs, data system provided a malleable structure for labelling numerous objects regarding the equivalent characteristics, data system laid a strong basis for constructing RSs.

In an archetypal data system, for the object representation, consider $U = \{x_1, x_2, \dots, x_n\}$ as a random universal discourse; for the characteristic exemplification, consider $A = \{a_1, a_2, \dots, a_m\}$ as a random attribute set. Then, the couple (U, A) is called a data system. Moreover, $a: U \rightarrow V_a$ for all $a \in \mathcal{A}_r$ and we characterize $a(x) \in V_a$.

Regarding a data system, all the attribute subsets $B \subseteq A$ encourage an indiscernibility relationship. $R_B = \{a(x) = a(y) | \forall a \in B, (x, y) \in U \times U\}$ that differences U into about correspondence modules as $U/R_B = \{[x]_B | x \in U\}$, where $[x]_B$ is the correspondence class encouraged by x under B , viz., $[x]_B = \{(x, y) \in R_A | y \in U\}$. For $X \subseteq U$ and $B \subseteq \mathcal{A}_r$. The lesser estimate of X is $\underline{R}_B(X) = \{[x]_B \subseteq X | x \in U\}$, while the higher estimate of X is

$R_B^-(X) = \{[x]_B \cap X \neq \emptyset | x \in U\}$. Next, we term the couple $(\underline{R}_B(X), R_B^-(X))$ An RS of X , and it is not challenging to discover $R_B(X)$ and $R_B^-(X)$ are the object subsets that surely and probably belong to X under B correspondingly.

According to $\underline{R}_B(X)$ and $R_B^-(X)$, Pawlak et al. suggest the conception of roughness and accuracy to achieve the hesitation of RST. Particularly, the accurateness is provided as the proportion of the $\underline{R}_B(X)$ and $R_B^-(X)$ as $\alpha_B(X) = (|\underline{R}_B(X)|/|R_B^-(X)|)$ While the RS is $\beta_B(X) = 1 - \alpha_B(X)$.

In NSF of RST, RNS and NRS are two important representations by incorporating NS with RS.

Assume U as a random universal discourse, and a correspondence relationship over U is R . For the NS A , the two estimates of A are given below:

$$\underline{Q}(A) = \{(x, \mu_{\underline{Q}(A)}(x), v_{\underline{Q}(A)}(x), \omega_{\underline{Q}(A)}(x)) | y \in [x]_R, x \in U\}; \quad (10)$$

$$\overline{Q}(A) = \{(x, \mu_{\overline{Q}(A)}(x), v_{\overline{Q}(A)}(x), \omega_{\overline{Q}(A)}(x)) | y \in [x]_R, x \in U\}, \quad (11)$$

Where $\mu_{\underline{Q}(A)}(x) = \bigwedge_{y \in [x]_R} \mu_A(y)$, $v_{\underline{Q}(A)}(x) = \bigvee_{y \in [x]_R} v_A(y)$, $\omega_{\underline{Q}(A)}(x) = \bigvee_{y \in [x]_R} \omega_A(y)$, $\mu_{\overline{Q}(A)}(x) = \bigvee_{y \in [x]_R} \mu_A(y)$, $v_{\overline{Q}(A)}(x) = \bigwedge_{y \in [x]_R} v_A(y)$, $\omega_{\overline{Q}(A)}(x) = \bigwedge_{y \in [x]_R} \omega_A(y)$. It is not challenging to discover $\underline{Q}(A)$ and $\overline{Q}(A)$ are NSs on U . Next, the couple $(\underline{Q}(A), \overline{Q}(A))$ Is known as an RNS of A .

Unlike RNS, which uses an indiscernibility relationship to estimate an NS notion, NRS aims to develop an estimate of NS under an NS estimate space. Then, the scientific formula of NRS is given as.

Assume U as a random universal discourse, R refers to an NS relationship on U . Next, for a random NS relationship, the couple (U, R) is known as an estimate space associated with NS. For the NS A , the two estimates of A under (U, R) are shown below:

$$\underline{R}(A) = \{(x, \mu_{\underline{R}(A)}(x), v_{\underline{R}(A)}(x), \omega_{\underline{R}(A)}(x)) | x \in U\}; \quad (12)$$

$$\overline{R}(A) = \{(x, \mu_{\overline{R}(A)}(x), v_{\overline{R}(A)}(x), \omega_{\overline{R}(A)}(x)) | x \in U\}, \quad (13)$$

Where $\mu_{\underline{R}(A)}(x) = \bigwedge_{y \in U} [\omega_R(x, y) \vee \mu_A(y)]$, $v_{\underline{R}(A)}(x) = \bigvee_{y \in U} [(1 - v_R(x, y)) \wedge v_A(y)]$, $\omega_{\underline{R}(A)}(x) = \bigvee_{y \in U} [\mu_R(x, y) \wedge \omega_A(y)]$, $\mu_{\overline{R}(A)}(x) = \bigvee_{y \in U} [\mu_R(x, y) \wedge \mu_A(y)]$, $v_{\overline{R}(A)}(x) = \bigwedge_{y \in U} [v_R(x, y) \vee v_A(y)]$, $\omega_{\overline{R}(A)}(x) = \bigwedge_{y \in U} [\omega_R(x, y) \vee \omega_A(y)]$. Next, the couple $(\underline{R}(A), \overline{R}(A))$ a NRS of A under (U, R) .

As stated by the RNS and NRS notions, it is easier to know the essential contribution lies in opening a new investigation course for NS and RST. Owing to the restrictions of NSs, RNS and NRS are intentional from the theoretic aspect:

Explore relationship between RNSs, RFSs, and FRSSs.

Study axiomatic methods to RNS and NRS from the definition.

Design data-motivated hybrid mechanisms by incorporating NSs with another comprehensive FS.

C. WOA-based Parameter Tuning

Lastly, the WOA is exploited for parameter fine-tuning, enhancing the system's accuracy. The WOA is a new metaheuristic optimization technique derived from the natural pursuing strategy of humpback whales [19]. This algorithm is enhanced by mimicking physical and biological phenomena. The three major steps are used to improve the location of candidate solution, such as encircle prey, spiral location update, and search for target to the location update. The steps are given in the following:

Encircle prey:

During prey encircling, humpback whales find the prey location, and then, they surround the prey. If $p < 0.5$ (with p being a random integer) and $|A|_r < 1$, it represents that the existing humpback whale has found the prey S_p and it is shrinking encirclement.

The location of candidate solution is updated using the following equations:

$$\vec{S}(t+1) = \vec{S}^*(t) - \vec{A}_r \cdot \vec{D} \quad (14)$$

$$\vec{D}_t = |\vec{B} \cdot \vec{S}^*(t) - \vec{S}(t)| \quad (15)$$

Where $\vec{S}(t+1)$ and $\vec{S}^*(t)$ are the existing and previous locations of whales at t iteration, and \vec{D} Indicates the interval between whale and prey.

\vec{B} and \vec{A}_r are coefficient vectors evaluated as follows:

$$\vec{A}_r = 2 \cdot \vec{a}_r \cdot \vec{e} + \vec{a}_r \quad (16)$$

$$\vec{B} = 2 \cdot \vec{e} \quad (17)$$

As the iteration number increases, the value of \vec{a}_r is linearly dropped from 2 to 0 at iteration and \vec{e} refers to the random vector within [0,1].

Spiral Position Update: When $p \geq 0.5$

The spiral formula is produced among the locations of whale and target for matching the movement of humpback whales as follows:

$$\vec{S}(t+1) = e^{(gl)} \cdot \cos(2\pi k) \cdot \vec{D}_t^* + \vec{S}^*(t) \quad (18)$$

$$\vec{D}_t^* = |\vec{S}^*(t) - \vec{S}(t)| \quad (19)$$

In the equations, a constant g shows the shape of logarithmic spiral, and l indicates the uniformly distributed random integer within [-1, 1].

Search for prey: When $p < 0.5$ and $|A_r| < 1$

Here, whale exploits random search to discover the prey based on the location of one another and it is mathematically modelled as follows:

$$\vec{S}(t+1) = \vec{S}_{(rand)} - \vec{A}_r \cdot \vec{D}_t \quad (20)$$

$$\vec{D} = |\vec{B} \cdot \vec{S}_{(rand)} - \vec{S}| \quad (21)$$

The fitness selection is the extensive feature manipulating the WOA performance. The parameter selection technique includes the solution encoding system for evaluating the effectiveness of the candidate solution. Now, the WOA considers performance as the key condition to devise the FF.

$$Fitness = \max(P) \quad (22)$$

$$P = \frac{TP}{TP + FP} \quad (23)$$

Where TP and FP are the true and the false positive values.

4. Performance Validation

In this section, the performance validation of the FCPM-NFRST methodology can be benchmark dataset [20]. The dataset contains 7027 samples under 1st year and 10173 samples under 2nd year with two classes represented in Table 1.

Table 1: Details on datasets

1st-year Dataset	
Class	No. of Instances
Financial Crisis	271
Non-Financial Crisis	6756
Total Instances	7027
2nd-year Dataset	
Class	No. of Instances

Financial Crisis	400
Non-Financial Crisis	9773
Total Instances	10173

In Table 2, the FCP results of the FCPM-NFRST method are depicted under 1st-year dataset. The result inferred that the FCPM-NFRST method has properly identified the financial and non-financial crises. With 70%TRAS, the FCPM-NFRST methodology gains average $accu_y$ of 93.87%, $sens_y$ of 93.87%. $spec_y$ of 93.87%, F_{score} of 93.11%, and MCC of 86.23%. In addition, with 30%TESS, the FCPM-NFRST method gains average $accu_y$ of 96.19%, $sens_y$ of 96.19%. $spec_y$ of 96.19%, F_{score} of 96.19%, and MCC of 92.39%.

Table 2: FCP outcome of FCPM-NFRST method under 1st-year dataset

Class	$Accu_y$	$Sens_y$	$Spec_y$	F_{Score}	MCC
TRAS (70%)					
Financial Crisis	88.36	88.36	99.39	86.75	86.23
Non-Financial Crisis	99.39	99.39	88.36	99.46	86.23
Average	93.87	93.87	93.87	93.11	86.23
TESS (30%)					
Financial Crisis	92.68	92.68	99.70	92.68	92.39
Non-Financial Crisis	99.70	99.70	92.68	99.70	92.39
Average	96.19	96.19	96.19	96.19	92.39

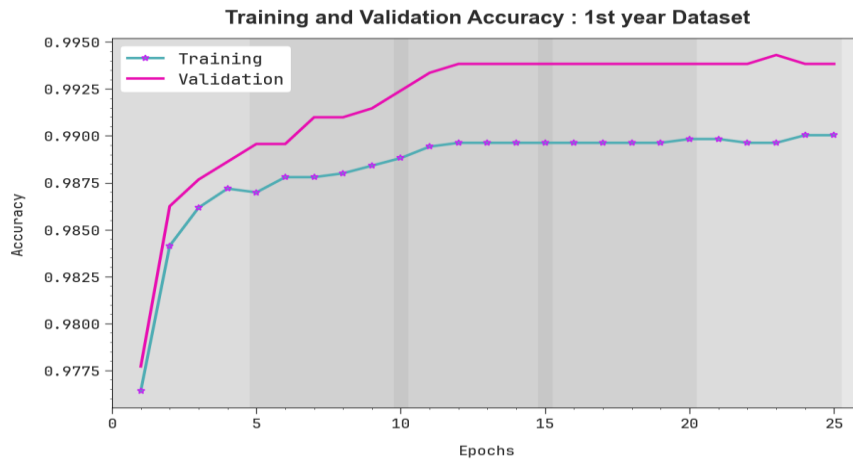


Figure 3. $Accu_y$ Curve of FCPM-NFRST method under 1st-year dataset

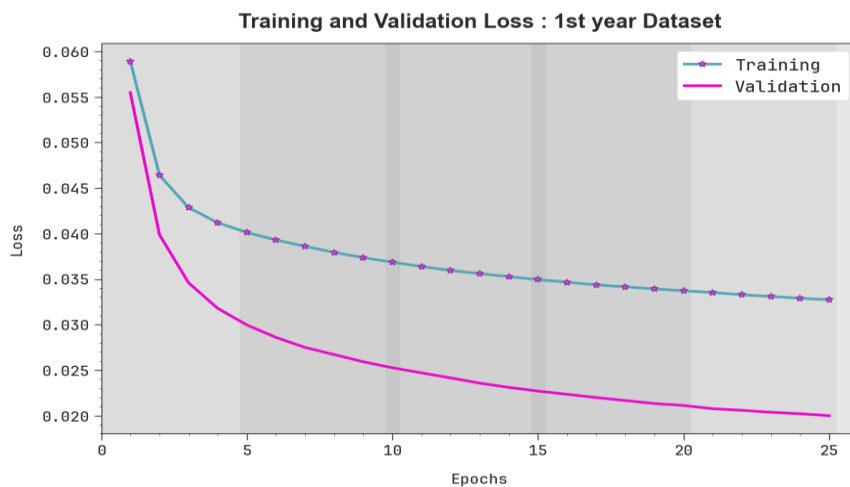


Figure 4. Loss curve of FCPM-NFRST method under 1st-year dataset

In Figure 3, the training and validation accuracy outcomes of the FCPM-NFRST method under 1st-year dataset are established. The accuracy value is calculated within the range of 0-25 epochs. The figure emphasized that the training and validation accuracy values display a growing tendency, which acquainted the capability of the FCPM-NFRST method with enriched performance over numerous iterations. Moreover, the training accuracy and validation accuracy remain closer over the epochs, which exhibits enhanced performance and indicates low minimal overfitting of the FCPM-NFRST method, guaranteeing reliable prediction on unseen samples.

In Figure 4, the training and validation loss graph of the FCPM-NFRST method under 1st-year dataset is demonstrated. The loss values are calculated within the range of 0-25 epochs. It is characterized that the training and validation accuracy values demonstrate a declining tendency, which notified the capability of the FCPM-NFRST calculated within the range of balancing a trade-off between data fitting and generalization. The continual decrease in loss values further guarantees the superior outcomes of the FCPM-NFRST method and tunes the predictive outcomes over time.

In Table 3, the FCP outcomes of the FCPM-NFRST method are described on 2nd year dataset. The outcome showed that the FCPM-NFRST method has appropriately recognized the financial and non-financial crisis. With 70%TRAS, the FCPM-NFRST method gains average $accu_y$ of 96.03%, $sens_y$ of 96.03%, $spec_y$ of 96.03%, F_{score} of 95.64%, and MCC of 91.28%. Furthermore, with 30%TESS, the FCPM-NFRST methodology gains average $accu_y$ of 96.06%, $sens_y$ of 96.06%, $spec_y$ of 96.06%, F_{score} of 95.00%, and MCC of 90.02%.

Table 3: FCP outcome of FCPM-NFRST method under 2nd-year dataset

Class	$Accu_y$	$Sens_y$	$Spec_y$	F_{score}	MCC
TRAS (70%)					
Financial Crisis	92.45	92.45	99.62	91.62	91.28
Non-Financial Crisis	99.62	99.62	92.45	99.66	91.28
Average	96.03	96.03	96.03	95.64	91.28
TESS (30%)					
Financial Crisis	92.62	92.62	99.49	90.40	90.02
Non-Financial Crisis	99.49	99.49	92.62	99.59	90.02
Average	96.06	96.06	96.06	95.00	90.02



Figure 5. $Accu_y$ Curve of FCPM-NFRST method under 2nd-year dataset

In Figure 5, the training and validation accuracy outcomes of the FCPM-NFRST method under 2nd-year dataset are established. The accuracy value is calculated within the range of 0-25 epochs. The figure emphasized that the training and validation accuracy values display a mounting tendency, which notified the capability of the FCPM-NFRST method with enriched performance over several iterations. Furthermore, the training accuracy and validation accuracy remain closer over the epochs, which exhibits enhanced performance and indicates low minimal overfitting of the FCPM-NFRST method, guaranteeing consistent prediction on unseen samples.

In Figure 6, the training and validation loss graph of the FCPM-NFRST model under 2nd year dataset is demonstrated. The loss values are calculated within the range of 0-25 epochs. It is represented that the training and validation accuracy values illustrate a declining tendency, which notified the capability of the FCPM-NFRST

method in balancing a tradeoff between data fitting and generalization. The repeated reduction in loss values further guarantees the superior performance of the FCPM-NFRST method and tunes the predictive outcomes over time.

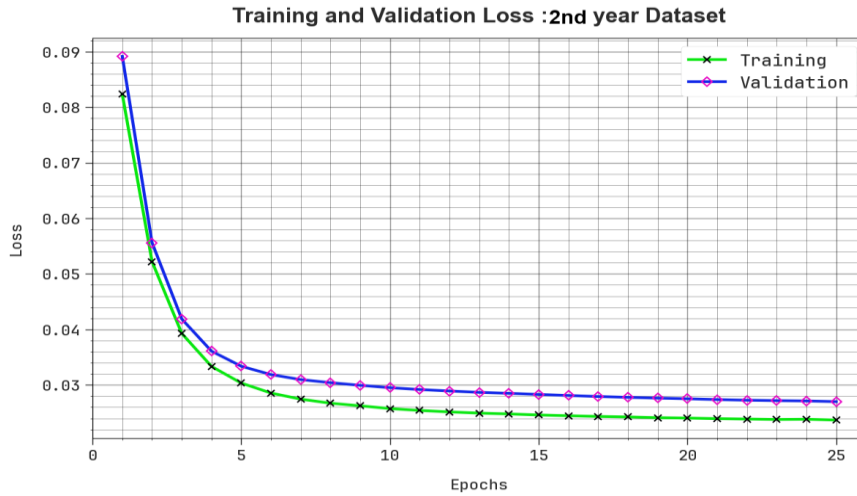


Figure 6. Loss curve of FCPM-NFRST method under 2nd-year dataset

In Table 4 and Figure 7, a widespread comparison study of the FCPM-NFRST method is demonstrated [21]. The outcomes specify that the RBF method has displayed ineffective performance. Along with that, the DT and Bagging methods have displayed somewhat increased outcomes. Meanwhile, the SVM, LR, MLP, and Olex-GA methods have established moderately closer outcomes. However, the FCPM-NFRST method outperforms the other techniques with higher $accu_y$ of 96.19%, $sens_y$ of 96.19%, $spec_y$ of 96.19%, and F_{score} of 96.19%.

Table 4: Comparative analysis of FCPM-NFRST method with other methods

Algorithm	$Accu_y$	$Sens_y$	$Spec_y$	F_{Score}
SVM Model	95.15	91.92	90.43	90.21
Bagging Model	95.07	94.06	95.62	91.29
Decision Tree	95.01	94.45	94.47	91.58
Logistic Regression	95.18	91.74	94.95	95.77
RBF Algorithm	92.90	92.43	94.28	94.36
MLP Algorithm	95.18	94.37	93.93	94.50
Olex-GA	95.19	93.01	91.21	90.11
FCPM-NFRST	96.19	96.19	96.19	96.19

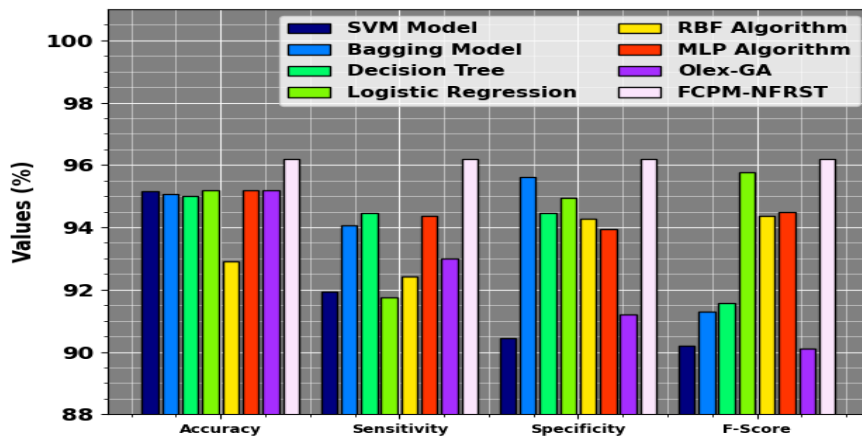


Figure 7. Comparative analysis of FCPM-NFRST method with other approaches

5. Conclusion

In this paper, we have developed a novel FCPM-NFRST methodology. The suggested FCPM-NFRST method for financial crises incorporates numerous forward-thinking systems to improve predictive performance. Primarily, the FFA-based feature selection to detect the fittest fiscal gauges. Consequently, the NFRST is exploited for strong cataloguing and successful management of vagueness and roughness in economic information. Lastly, the WOA is exploited for parameter fine-tuning, enhancing the system's accuracy. Investigational study displays that the FCPM-NFRST ensemble mechanism is more robust and superior than its complements. Accordingly, this study powerfully suggests that the suggested FCPM-NFRST method is very competitive with conventional and other existing algorithms.

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