Towards Sustainable Economy: Boosting Financial Credit Risk Forecasting Using Bipolar Single-Valued Neutrosophic Graph Sets Approach

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Abstract

A neutrosophic set (NS) contains 3 modules such as the degree of truth (T), degree of falsity (F), and degree of indeterminacy (I). While fuzzy graphs (FG) occasionally fall short of providing optimum outcomes, the NS and neutrosophic graphs (NG) provide a strong substitute, which efficiently handles the uncertainties related to indeterminate and inconsistent data in real-life scenarios. Conversely, bipolar neutrosophic methods, which account for both negative and positive effects, deliver a more flexible and applicable technique. Financial crisis prediction (FCP) is inherent in the detection of major social and economic impacts that crises of financial might hold on a global measure. It generally outcomes in vast financial losses, redundancy, and losses in values of assets that lead to significantly affected individuals and businesses. In recent times, the credit risk prediction methods have aided businesses in resolving whether to award credit to users who applied. This paper presents the Financial Credit Risk Forecasting Using Bipolar Single-Valued Neutrosophic Graph Sets Approach (FCRF-BSVNGSA) method. The main intention of the FCRF-BSVNGSA method is to develop an effective method for financial credit risk prediction using advanced methods. At first, the data normalization stage utilizes Z-score normalization for converting the input data into a beneficial format. Furthermore, for the financial credit risk classification process, the proposed FCRF-BSVNGSA model employs the bipolar single-valued neutrosophic graphs (BSVNG) approach. Finally, the multi-objective hippopotamus optimization (MOHO) approach fine-tunes the hyperparameter values of the BSVNG model optimally and results in superior classification performance. An extensive simulation of the FCRF-BSVNGSA approach is performed under the Statlog (German Credit Data) dataset. The experimental validation of the FCRF-BSVNGSA approach portrayed a superior accuracy value of 95.59% over exisitng techniques.

Keywords: Financial Credit Risk Forecasting; Data Normalization; Fuzzy Graphs; Bipolar Neutrosophic Set; Single-Valued Neutrosophic Graph

1. Introduction

The most effective tools for modeling uncertainty in making a decision problem are the NS and its extension lead, such as interval NS (INS), complex NS (CNS), and interval complex NS (ICNS) [1]. An effective device for vagueness and demonstrating uncertainty in making the decision is the NS, which is the other generality of standard set, intuitionistic fuzzy set (IFS), and fuzzy set (FS) by adding triplet kinds of truth, falsity, and indeterminacy of a proved statement [2]. It is employed in various processes of decision-making that is. On the other hand, to adapt NS to the above real difficult cases, INS and CNS is proposed suitably. The financial crisis became a critical

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problem for the globe [3]. In recent years, more small and medium enterprises (SMEs) previously weakened by the growing collapse, and publicized nil losses or profits. Widely some major bankruptcies are methodically published and the financial suffering spreads out to each type of firm across more businesses [4]. The big loss arising out of the bankruptcies is in the lead to major disapproval of financial institutions owing to the unsuitable assessments of credit hazard [5].

The governments can be forced to apply rescue strategies for the methods of banking with much valuable credit hazard assessments. It is a challenging and main problem for banking and financial institutions to assess client presentation [6]. For this purpose, financial credit hazard estimates help as the motivation to value the credit access or possible industry flop of clients to create prior acts before the real financial crisis. Financial crises can lead to unemployment, losses in asset values, and huge economic losses, resulting in considerable individuals and affected businesses [7]. It is necessary to advance reliable and early predictive systems for financial or company entities to predict the possible hazards of the status of a business [8]. Wrongly making decisions in the company may result in bankruptcy or an economic flop and vendors, affecting investors, clients, etc [9]. These days, AI technologies and statistics are utilized for the recognition of FCP. AI is employed in several methods in FCP that are based on a classical which forecasts whether the financial company can undergo a crisis or not [10]. Similarly, earlier research concentrated on deep learning (DL), machine learning (ML), and arithmetical models for estimating the financial grade of an industry.

This paper presents the Financial Credit Risk Forecasting Using Bipolar Single-Valued Neutrosophic Graph Sets Approach (FCRF-BSVNGSA) method. The main intention of the FCRF-BSVNGSA method is to develop an effective method for financial credit risk prediction using advanced methods. At first, the data normalization stage utilizes Z-score normalization for converting the input data into a beneficial format. Furthermore, for the financial credit risk classification process, the proposed FCRF-BSVNGSA model employs the bipolar single-valued neutrosophic graphs (BSVNG) approach. Finally, the multi-objective hippopotamus optimization (MOHO) approach fine-tunes the hyperparameter values of the BSVNG model optimally and results in superior classification performance. An extensive simulation of the FCRF-BSVNGSA approach is performed under the Statlog (German Credit Data) dataset.

A. Contribution of the Study

The major contribution of the FCRF-BSVNGSA approach is given below.

The FCRF-BSVNGSA model utilizes Z-score normalization to standardize the input data, ensuring all features have a mean of zero and a standard deviation of one. This step improves the consistency of the data and prevents any features with larger ranges from dominating the results. As a result, the performance of the model is more balanced and reliable.

The FCRF-BSVNGSA approach employs the BSVNG-based classification model to handle uncertainty and imprecision in the data. This approach allows for more accurate representation of complex relationships within the dataset. Consequently, it results in improved decision-making and more reliable predictions.

The FCRF-BSVNGSA methodology incorporates the MOHO model for tuning process to optimize its parameters across multiple objectives. This process enables the simultaneous improvement of both predictive accuracy and computational efficiency. As a result, the model attains a more effectual balance between performance and resource utilization.

The novelty of the FCRF-BSVNGSA method is in integrating BSVNG technique for classification with MOHO model. This integration allows the model to effectually manage uncertainty in decision-making while optimizing multiple objectives simultaneously. The result is an improved performance that enhances both predictive accuracy and computational efficiency.

2. A Brief Survey on Financial Risk Prediction Models

Ji and Li [11] project a dynamic financial risk prediction method for companies depending upon gradient-boosting decision trees (DT) for enhancing forecasting precision and adjustability. The projected methodology parameter was enhanced over the gradient optimizer by utilizing the sparrow search algorithm. Cui and Yao [12] introduce the PSO-SDAE method, an innovative and advanced model for predicting financial risk. By integrating optimization algorithms and cutting-edge noise reduction features, the projected method considerably improves the reliability and accuracy of financial risk predictions. Particularly, the presented methodology overtakes conventional predicting models by tackling the requirement for deciding on the quickly developing setting of economic risk management. Mojdehi et al. [13] projected an innovative hybrid Graph Neural Network (GNN) and Topological Data Analysis (TDA) to enhance credit risk assessment in SCF. By employing BallMapper (BM) topological data analysis method and network-based aspects, the projected method offers better understanding of credit risk influences, improving the precision and reliability of credit risk assessment for SMEs.

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Amarnadh and Moparthi [14] develop credit risk evaluation in the banking area utilizing an Adaptive Binarized Spiking Marine Predators Neural Network (ABSMPNN) for precise recognition of client credit qualities in the short term. The concentration stage of VCHA effectually attains the collection of appropriate aspects from the noisy and inappropriate ones. Alamsyah et al. [15] present an innovative model utilizing sophisticated ML methodologies and social media analytics to evaluate the creditworthiness of customers without conventional collateral assets and credit histories. Traditional credit scoring models have a tendency to rely heavily on central bank credit data, particularly conventional co-lateral abilities like savings accounts or property. This method employs psycholinguistics, personality, demographics, and social networking data from the profiles of LinkedIn to advance the prediction techniques for a wide-ranging economic dependability evaluation. Zhang and Wang [16] project ensemble learning to build a robust credit risk prediction method through combination of many fundamental ML methodologies. There are 3 classification-based ML methods such as SVM, radial basis function, and ANN models, and "voting" approach was employed to combine into an innovative strong classifier.

A. Limitations and Research Gap

Despite the improvements in financial risk and credit risk prediction models, various limitations still exist. Many models, such as those based on gradient-boosting DTs or ensemble learning, may not effectually handle the complex and dynamic nature of financial markets, resulting in suboptimal performance in rapidly changing conditions. Furthermore, while methods such as PSO-SDAE and hybrid models enhance accuracy, they often depend on computationally expensive optimization techniques, which can limit scalability. The integration of social media and psycholinguistics data for creditworthiness assessment is innovative but may raise concerns regarding data privacy and reliability. Moreover, the reliance on historical financial data and conventional collateral information in some models does not fully address the needs of unbanked or underbanked populations. Lastly, many models are designed for specific contexts, such as SMEs or banks, limiting their general applicability across diverse industries or regions. Further research is required to develop more adaptable, scalable, and privacy-preserving methods for broader financial risk prediction.

3. The Proposed Method

In this study, a novel FCRF-BSVNGSA technique is proposed. The primary objective of FCRF-BSVNGSA technique is to develop an effective model for financial credit risk prediction using advanced methods. It contains three various kinds of processes involved ass z-score normalization, BSVNG-based classification, and MOHO-based parameter tuning. Fig. 1 signifies the complete workflow of the FCRF-BSVNGSA model.

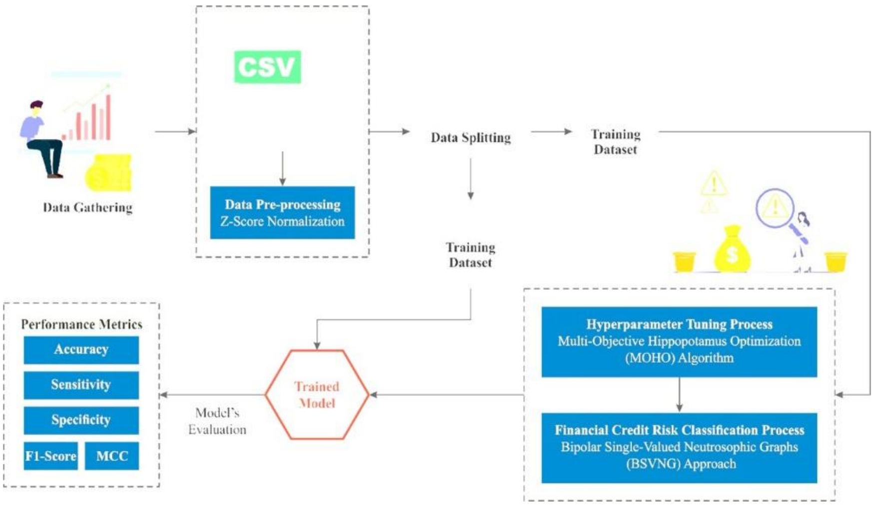

Figure 1. Overall flow of FCRF-BSVNGSA approach

The working process involves three steps as listed below.

- Z-score based normalization
- BSVNG based prediction
- MOHO based parameter selection

A. Data Normalization: Z-score

At first, the data normalization step applies Z-score normalization for converting an input data into a beneficial format. Z-score normalization also known as standardization, is a numerical model applied in financial credit risk

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prediction to convert data into a typical scale by a mean of 0 and a standard deviation of 1 [17]. It aids in managing varying measures in financial data and makes sure fair contrasts across dissimilar risk indicators. By transforming raw credit risk features into normalized scores, this normalization improves stability and accuracy of model. It also diminishes an impact of outliers, which are general in financial datasets. This model is mainly beneficial in credit risk methods depending upon ML and statistical techniques. Standardized data increases convergence in optimizer models, which leads to better performance of predictive.

B. Model Selection

For the financial credit risk classification process, the proposed FCRF-BSVNGSA model utilizes the BSVNG approach. This part recollects some basic definitions related to BFG, BSVNG along dominance important for this study [18].

Definition: 3.1

A BFG using a finite set X as the primary set represents pairs of $G = (V, E)$, wherein $V = (\mu_V^+, \mu_V^-)$ signifies a bi-polar fuzzy set (FS) on X, however $E = (\mu_E^+, \mu_E^-)$ designates a bi-polar fuzzy relation on X given that $\mu_E^+(v_m v_n) \leq \mu_v^+(v_m) \wedge \mu_v^+(v_n)$ and $\mu_E^-(v_m v_n) \geq \mu_v^+(v_m) \vee \mu_v^+(v_n)$ whereas $v_m v_n \in E$. They appeal $V = (\mu_V^+, \mu_V^-)$ the bi-polar fuzzy vertex set of X, whereas $E = (\mu_E^+, \mu_E^-)$ indicates the bi-polar fuzzy edge set of X.

Definition: 3.2

A bi-polar NS A about nonempty set X mentions an objective of the method.

$$A = \{\langle x, T_A^+(x), I_A^+(x), F_A^+(x), T_A^-(x), I_A^-(x), F_A^-(x)\rangle : x \in X\},$$

Whereas$T_A^+, I_A^+, F_A^+ : X \to [0,1]andT_A^-, I_A^-, F_A^- : X \to [-1,0]$.Now, the positive values $T_A^+(x), I_A^+(x), F_A^+(x)$ expressed the truth, indeterminacy in addition to false-memberships amounts of the component $x \in X$, correspondingly, but $T_A^-(x), I_A^-(x), F_A^-(x)$ state the hidden counter properties of the indeterminacy, truth, and false-memberships degrees of the component $x \in X$, consequently, which is equivalent to the bi-polar NS A.

Definition: 3.3

Assume $A = (T_A^+, I_A^+, F_A^+, T_A^-, I_A^-, F_A^-)$ and $B = (T_B^+, I_B^+, F_B^+, T_B^-, I_B^-, F_B^-)$ remain bi-polar NG on a set X. When $B = (T_B^+, I_B^+, F_B^+, T_B^-, I_B^-, F_B^-)$ signify a bi-polar Neutrosophic relation on $A = (T_A^+, I_A^+, F_A^+, T_A^-, I_A^-, F_A^-)$, formerly

$$T_B^+(xy) \leq \min(T_A^+(x), T_A^+(y)), I_B^+(xy) \geq \max(I_A^+(x), I_A^+(y)), F_B^+(xy) \geq \max\left(F_A^+(x), F_A^+(y)\right),$$

$$T_B^-(xy) \geq \max(T_A^-(x), T_A^-(y)), I_B^-(xy) \leq \min(I_A^-(x), I_A^-(y)), F_B^-(xy) \leq \min(F_A^-(x), F_A^-(y)), \forall x, y \in X.$$

Definition: 3.4

Assume that $G = (V, E)$ represents a BSVNG whereas $x, y \in V$ in G. Later demonstrate that x leads y if

$$T_E^+(xy) = T_V^+(\chi) \wedge T_V^+(y), I_E^+(xy) = I_V^+(x) \vee I_V^+(y), F_E^+(xy) = F_V^+(x) \vee F_V^+(y),$$

$$T_E^-(xy) = T_V^-(x) \vee T_V^-(y), I_E^-(xy) = I_V^-(x) \wedge I_V^-(y), F_E^-(xy) = F_V^-(x) \wedge F_V^-(y) .$$

Definition:4.1

A graph of the type $\tilde{G} = (V, E, \mu^+, \gamma^+, \sigma^+, \mu^-, \gamma^-, \sigma^-, \mu_1^+, \gamma_1^+, \sigma_1^+, \mu_1^-, \gamma_1^-, \sigma_1^-)$ is named double dominating BSVNG, whereby $\mu_1^+ : V \to [0,1]$, $\gamma_1^+ : V \to [0,1]$, and $\sigma_1^+ : V \to [0,1]$, symbolizes a positive membership, indeterminacy, and non-membership degrees, $\mu_1^- : V \to [-1,0]$, $\gamma_1^- : V \to [-1,0]$, and $\sigma_1^- : V \to [-1,0]$, designates a negative membership, indeterminacy, and non-membership degrees described given that

$$\mu_1^+(v_m) = \min[\mu^+(v_m, v_n)], \gamma_1^+(v_m) = \max[\gamma^+(v_m, v_n)], \sigma_1^+(v_m) = \max[\sigma^+(v_m, v_n)], \quad \mu_1^-(v_m) = \max[\mu^-(v_m, v_n)], \gamma_1^-(v_m) = \min[\gamma^-(v_m, v_n)], \sigma_1^-(v_m) = \min[\sigma^+(v_m, v_n)].$$

Definition: 4.2

For every BSVNG, $\tilde{G} = (V, E, \mu^+, \gamma^+, \sigma^+, \mu^-, \gamma^-, \sigma^-, \mu_1^+, \gamma_1^+, \sigma_1^+, \mu_1^-, \gamma_1^-, \sigma_1^-)$, a subset $\widetilde{D}_d \subseteq V$ is identified as double dominating set (DDS) in $\tilde{G}$ given that every vertex in $V - \widetilde{D}_d$ is dominated by fully dual vertices in $\widetilde{D}_d$. The reduced cardinality of each DDS of $\tilde{G}$ is recognized as the double domination number of $\tilde{G}$, characterized by $\gamma_{D_d}^N(\tilde{G})$.

Definition: 4.3

Assume $\tilde{G} = (V, E, \mu^+, \gamma^+, \sigma^+, \mu^-, \gamma^-, \sigma^-, \mu_1^+, \gamma_1^+, \sigma_1^+, \mu_1^-, \gamma_1^-, \sigma_1^-)$ signify a double-dominating BSVNG. Assume $u, v \in V$. Now, u dominates v in $\tilde{G}$. Given that stronger edges occur from u to v.

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Definition: 4.4

Assume $\tilde{G} = (V, E, \mu^+, \gamma^+, \sigma^+, \mu^-, \gamma^-, \sigma^-, \mu_1^+, \gamma_1^+, \sigma_1^+, \mu_1^-, \gamma_1^-, \sigma_1^-)$ indicate a two dominating BSVNG. Therefore, the adjacency matrix as regards $\tilde{G}$ is stated as $A_{\tilde{D}_d}(\tilde{G}) = [d_{mn}]$, wherein

$$d_{mn} = \begin{cases} \begin{pmatrix} \mu_{mn}^+, \gamma_{mn}^+, \sigma_{mn}^+ \\ \mu_{mn}^-, \gamma_{mn}^-, \sigma_{mn}^- \end{pmatrix} & if\,(v_m, v_n) \in E \\ \begin{pmatrix} 1,1,1, \\ -1,-1,-1 \end{pmatrix} & if\, m = n \text{ and } v_m \in D_{\tilde{D}_d} \\ \begin{pmatrix} 0,0,0, \\ 0,0,0 \end{pmatrix} & otherwise \end{cases}$$

These dominating bi-polar matrices of the single-valued neutrosophic adjacency, $A_{\tilde{D}_d}(\overline{G})$ might be stated as $A_{\tilde{D}_d}(\tilde{G}) = (\mu_{\tilde{D}_d}^+(\tilde{G}), \gamma_{\tilde{D}_d}^+(\tilde{G}), \sigma_{\tilde{D}_d}^+(\tilde{G}), \mu_{\tilde{D}_d}^-(\tilde{G}), \gamma_{\tilde{D}_d}^-(\tilde{G}), \sigma_{\tilde{D}_d}^-(\tilde{G}))$ wherein

$$\mu_{\tilde{D}_d}^+(\tilde{G}) = \begin{cases} \mu_{mn}^+ \; if\; (v_m, v_n) \in E \\ 1 \; if \; m = n \; and \; v_j \in \tilde{D}_d, \\ 0 \; otherwise \end{cases}$$

$$\gamma_{\tilde{D}_d}^+(\tilde{G}) = \begin{cases} \gamma_{mn}^+ \; if\; (v_m, v_n) \in E \\ 1 \; if \; m = n \; and \; v_m \in \tilde{D}_d, \\ 0 \; otherwise \end{cases}$$

$$\sigma_{\tilde{D}_d}^+(\tilde{G}) = \begin{cases} \sigma_{mn}^+ \; if\; (v_m, v_n) \in E \\ 1 \; if \; m = n \; and \; v_m \in \tilde{D}_d, \\ 0 \; otherwise \end{cases}$$

$$\mu_{\tilde{D}_d}^-(G) = \begin{cases} \mu_{mn}^- \; if\; (v_m, v_n) \in E \\ -1 \; if \; m = n \; and \; v_m \in \tilde{D}, \\ 0 \; oiherwise \end{cases}$$

$$\gamma_{\tilde{D}_d}^-(\tilde{G}) = \begin{cases} \gamma_{mn}^- \; if\; (v_m, v_n) \in E \\ -1 \; if \; m = n \; and \; v_m \in \tilde{D}_d, \\ 0 \; otherwise \end{cases}$$

$$\sigma_{\tilde{D}_d}^-(\tilde{G}) = \begin{cases} \sigma_{mn}^- \; if\; (v_m, v_n) \in E \\ -1 \; if \; m = n \; and \; v_m \in \tilde{D}_d. \\ 0 \; otherwise \end{cases}$$

Definition: 4.5

The spectrum regarding the matrix of adjacency of a double-dominating BSVNG $\tilde{G}$ is represented as $\left(S_{\tilde{D}_d}^{\mu^+}, S_{\tilde{D}_d}^{\gamma^+}, S_{\tilde{D}_d}^{\sigma^+}, S_{\tilde{D}_d}^{\mu^-}, S_{\tilde{D}_d}^{\gamma^+}, S_{\tilde{D}_d}^{\sigma^-}\right)$, where $S_{\tilde{D}_d}^{\mu^+}, S_{\tilde{D}_d}^{r^+}, S_{\tilde{D}_d}^{\sigma^+}, S_{\tilde{D}_d}^{\mu^-}, S_{\tilde{D}_d}^{r^-}, S_{\tilde{D}_d}^{\sigma^-}$ represents collections of eigenvalues of $\mu_{\tilde{D}_d}^+(\tilde{G}), \gamma_{\tilde{D}_d}^+(\tilde{G}), \sigma_{\tilde{D}_d}^+(\tilde{G}), \mu_{\tilde{D}_d}^-(\tilde{G}), \gamma_{\tilde{D}_d}^-(\tilde{G})$, and $\sigma_{\tilde{D}_d}^-(\tilde{G})$, correspondingly.

Definition: 4.6

The energy of the double-dominating BSVNG $\tilde{G} = (V, E, \mu^+, \gamma^+, \sigma^+, \mu^-, \gamma^-, \sigma^-, \mu_1^+, \gamma_1^+, \sigma_1^+, \mu_1^-, \gamma_1^-, \sigma_1^-)$ was described as

$$E_{\tilde{D}_d}(\tilde{G}) = \left(E\left(\mu_{\tilde{D}_d}^+(\tilde{G})\right), E\left(\gamma_{\tilde{D}_d}^+(\tilde{G})\right), E\left(\sigma_{\tilde{D}_d}^+(\tilde{G})\right), E\left(\mu_{\tilde{D}_d}^-(\tilde{G})\right), E\left(\gamma_{\tilde{D}_d}^-(\tilde{G})\right), E\left(\sigma_{\tilde{D}_d}^-(\tilde{G})\right)\right)$$

$$= \left(\sum_{p=1}^{n} |\zeta_p|, \sum_{p=1}^{n} |\tau_p|, \sum_{p=1}^{n} |v_p|, \sum_{p=1}^{n} |\theta_p|, \sum_{p=1}^{n} |\xi_p|, \sum_{p=1}^{n} |\varepsilon_p|\right)$$

Whereas $S_{\tilde{D}_d}^{\mu^+} = \{\zeta_p\}_{p=1}^n, S_{\tilde{D}_d}^{\gamma^+} = \{\tau_p\}_{p=1}^n, S_{\tilde{D}_d}^{\sigma^+} = \{\iota)_p\}_{p=1}^n, S_{\tilde{D}_d}^{\mu^-} = \{\theta_p\}_{p=1}^n, S_{\tilde{D}_d}^{\gamma^-} = \{\xi_p\}_{p=1}^n$ and $S_{\tilde{D}_d}^{\sigma^-} = \{\varepsilon_p\}_{p=1}^n$.

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C. Algorithmic Selection for Parameter Tuning

Eventually, the MOHO technique fine-tunes the hyperparameter values of the BSVNG technique optimally and results in better classification performance. The MOHO model is a population-based meta-heuristic influenced by the hunting and social behaviours of hippopotamuses [19]. This model is separated into 3 stages: defense against predators, exploitation, and exploration. Every stage replicates their behaviors monitored by hippopotamuses during their connections in ponds and rivers while opposed by hunters.

Every solution related to a vector X_i in the searching area, here $i = 1,2,\dots,N_i$, with N depicting the entire searching agents. The location of every hunting agent X_i is initialized based on the equation.

$$X_{ij} = lb_j + r_j * (ubj - lbj), for\ j = 1,2,\dots.,d \tag{1}$$

Where, lb_j and ub_j signify the lower and upper limits of the searching area for the jth size, r_j denotes a consistently distributed arbitrary number between zero and one, and d represents the dimensionality concerns. The fitness value and equivalent location from the primary population are stored as X_{best} and f_{best}, correspondingly.

Phase1: Exploration

In the level of exploration, the searching agents upgrade their location depending upon connections with the prevailing individual and an arbitrarily chosen agent groups. The location of every agent is upgraded:

1. First Position Update:

The initial location upgrade X_{P1} is affected by the dominant hippopotamus:

$$X_{P1} = X_i + r_1 * (X_{best} - I_1 * X_i) \tag{2}$$

Here: r_1 is a random scalar, and I_1 is an arbitrarily selected value from the set $\{1,2\}$.

2. Second Position Update:

Another upgrade X_{P2} based on the mean spot of an arbitrary community of searching agents X_{mean} and the foremost hippos:

$$X_{P2} = \begin{cases} X_i + A * (X_{best} - I_2 * X_{mean}), & if\ T > 0.6 \\ X_i + B * (X_{meon} - X_{best}), & if\ rand() > 0.5 \\ lb + r_2 * (ub - lb), & otherwise \end{cases} \tag{3}$$

Here r_2 depicts a randomly formed scalar, A, and B are arbitrary vectors created from the integration of arbitrary integers. $T = exp(-r/Max\_iter)$ manages the transition among exploitation and exploration. I_2 signifies integer values of l or 2 based on the hippo's location in the level of exploration. t represents the existing iteration, and Max_iter specifies the maximal iteration counts. T manages the evolution of models.

3. Fitness Comparison:

Afterwards upgrading the location of X_{P2} and X_{Pl} the novel location is assessed utilizing the FF. The searching agent maintains the finest solution:

$$X_i = \begin{cases} X_{P1}, & if\ f\ X_{p1} < f(x_i) \\ X_{P2}, & if\ f\ X_{p2} < f(x_i) \end{cases} \tag{4}$$

Phase2: Defense Against Predators

During the level, the searching agent upgrades their location to protect itself from hunters and arbitrarily creates points in the hunting area. The location of predator $X_{predator}$ is created:

$$X_{predator} = lb + r_3 * (ub - lb) \tag{5}$$

Every search agent upgrades its location X_{P3} depend upon its distance to Levy fight mechanism and predator:

$$X_{P3} = \begin{cases} RL * X_{predaтor} + \dfrac{b}{c - b\cos(l)} * \dfrac{1}{distance2Leader}) & if\ f\ (X_{predaтor}) < f(Xi) \\ RL * X_{predator} + \dfrac{b}{c - b\cos(l)} * \dfrac{1}{2 * distance2Leader + r4}, & otherwise \end{cases} \tag{6}$$

RL means distribution of Levy that presents arbitrariness in the process of hunting and b, c, d, and l symbolize randomly generated numbers managing the hunter's influence. r_3 and r_4 in Eqs. (5) & (6) represent consistently

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dispersed arbitrary numbers among (0,1), employed for regulating randomness in the individual movement. ub and lb signifies the upper and lower bound of the searching area for provided decision variables.

Phase3: Exploitation stage (Escape from the Predator)

In this stage, the hunting agent optimizes their location to run away from hunters and travel to the optimum solutions.

$$X_{P4} = X_i + r_5 * \left(\frac{lb}{t} + D * \left(\frac{ub}{t} - \frac{lb}{t}\right)\right) \tag{7}$$

Here r_5 represents an arbitrary scalar, and t is existing iterations. D in Eq. (7) depicts an arbitrary vector originating from pre-defined changes like rotation, refection, or scaling. It fine-tunes the magnitude and direction of movement for female or immature hippopotamuses. It improves the adjustability of a model to different optimizer settings.

A new location is recognized when it leads to an enhancement in fitness:

$$X_i = \{X_{P4}, if\ f(X_{P4}) < f(X_i) \tag{8}$$

The model endures to iterate over the defense, exploitation, and exploration stages until the maximal iteration counts Max_iter is achieved. The finest solution X_{best} and equivalent fitness value f_{best} it came back to output. The model of MOHO matches exploitation and exploration over its 3 stages, guaranteeing that the searching agents travel the hunting area extensively while converging to the globally optimal.

The MOHO approach originates a fitness function (FF) for attaining an enhanced performance of classification. To signify an enhanced candidate solution performance, the FF states a positive numeral. Here, the classification rate of error reduction was determined by FF. The mathematical formulation is shown below:

$$fitness(x_i) = ClassifierErrorRate(x_i) = \frac{no. of\ misclassified\ samples}{Total\ no. of\ samples} \times 100 \tag{9}$$

4. Performance Validation

The simulation validation of FCRF-BSVNGSA technique is inspected under the Statlog (German Credit Data) dataset [20]. The dataset was accessed on 27 Feb. 2025. The dataset consists of 1000 instances, classified into two classes: "Financial Crisis" with 300 instances and "Non-Financial Crisis" with 700 instances.

Fig. 2 displays the classifier analysis of the FCRF-BSVNGSA method. Figs. 2a-2b exemplifies the confusion matrices through specific identification and classification of each class below 70%TRAPHA and 30%TESPHA. Fig. 2c displays the PR inspection, notifying higher outcomes through distinct class labels. Finally, Fig. 2d represents the ROC examination, signifying proficient outcomes through high values of ROC for several classes.

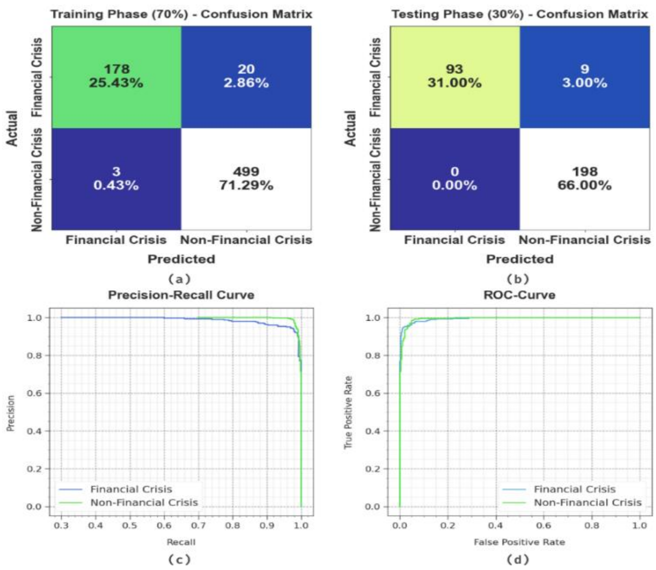

Figure 2. Classifier outcome of (a-b) 70% and 30% confusion matrices and (c-d) curves of PR and ROC

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Fig. 3 examine the financial credit risk prediction of FCRF-BSVNGSA methodology below 70%TRAPHA and 30%TESPHA. The performances stated that the FCRF-BSVNGSA methodology suitably classified all the samples. Using 70%TRAPHA, the FCRF-BSVNGSA method delivers average $accu_y$ of 94.65%, $sens_y$ of 94.65%, $spec_y$ of 94.65%, $F1_{score}$ of 95.84%, and MCC of 91.86%. Additionally, on 30%TESPHA, the FCRF-BSVNGSA approach provides average $accu_y$ of 95.59%, $sens_y$ of 95.59%, $spec_y$ of 95.59%, $F1_{score}$ of 96.58%, and MCC of 93.39%.

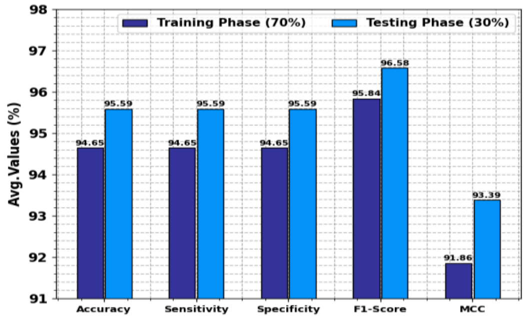

Figure 3. Average of FCRF-BSVNGSA model under 70%TRAPHA and 30%TESPHA

In Fig. 4, the TRAN $accu_y$ and VALN $accu_y$ performances of the FCRF-BSVNGSA technique are depicted. The values of $accu_y$ are computed across a time of 0-25 epochs. The figure underscored that the values of TRAN and VALN $accu_y$ expresses a growing propensity, indicating the capacity of the FCRF-BSVNGSA approach with maximum performance across numerous repetitions. Afterward, the TRAN and VALN $accu_y$ values remain close through the epochs, notifying diminished overfitting and presenting superior performance of the FCRF-BSVNGSA approach, which guarantees reliable calculation on hidden samples.

Figure 4. $Accu_y$ Curve of FCRF-BSVNGSA model

In Fig. 5, the TRANLOS and VALNLOS graph of the FCRF-BSVNGSA methodology is revealed. The values of loss are computed through a time of 0-25 epochs. It is exemplified that the values of TRANLOS and V VALNLOS represent a declining propensity, which indicates the competency of the FCRF-BSVNGSA methodology in corresponding to an equilibrium between generalization and data fitting. The progressive dilution in values of loss as well as securities the superior performance of the FCRF-BSVNGSA approach and tune the calculation results after a while.

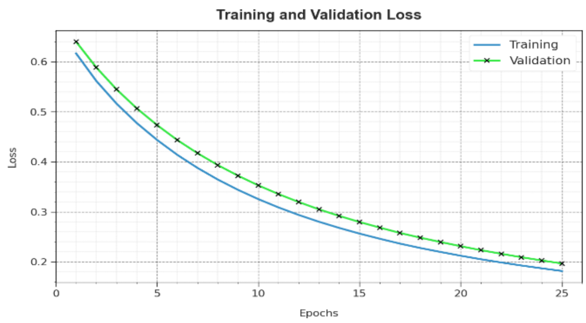

Figure 5. Loss curve of FCRF-BSVNGSA model

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Fig. 6 studies the $sens_y$, and $spec_y$ analysis of FCRF-BSVNGSA model with existing methodologies [21]. According to $sens_y$, the FCRF-BSVNGSA technique has maximum $sens_y$ of 95.59% although the HHPODL-FCP, QABO-LSTM-RNN, LSTM-RNN, ACO, MLP, SVM, and AdaBoost approaches have gained lower $sens_y$ of 93.59%, 87.25%, 82.21%, 78.32%, 73.89%, 72.71%, and 71.40%, correspondingly. In addition, according to $spec_y$,the FCRF-BSVNGSA technique has superior $spec_y$ of 95.59% although the HHPODL-FCP, QABO-LSTM-RNN, LSTM-RNN, ACO, MLP, SVM, and AdaBoost approaches have reached diminished $spec_y$ of 94.04%, 93.59%, 88.56%, 69.32%, 66.91%, 66.44%, and 61.35%, correspondingly.

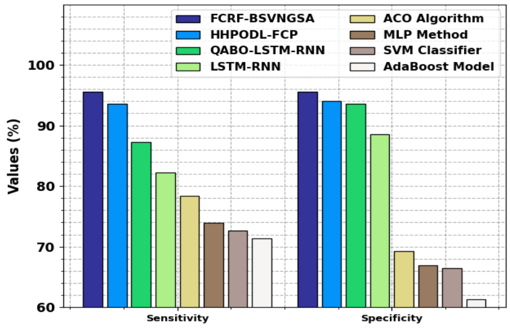

Figure 6. $Sens_y$, and $Spec_y$ outcome of FCRF-BSVNGSA technique with existing models

Fig. 7 examines $accu_y$, and $F1_{score}$ analysis of FCRF-BSVNGSA model with existing methodologies. With $accu_y$, the FCRF-BSVNGSA model has increased $accu_y$ of 95.59% although the HHPODL-FCP, QABO-LSTM-RNN, LSTM-RNN, ACO, MLP, SVM, and AdaBoost models have attained minimal $accu_y$ of 94.93%, 91.97%, 84.59%, 75.79%, 70.97%, 71.20%, and 67.55%, respectively. Afterwards, using $F1_{score}$,the FCRF-BSVNGSA method has increased $F1_{score}$ of 96.58% although the HHPODL-FCP, QABO-LSTM-RNN, LSTM-RNN, ACO, MLP, SVM, and AdaBoost models have gained diminished $F1_{score}$ of 93.73%, 90.12%, 88.76%, 85.41%, 75.13%, 71.79%, and 71.29%, correspondingly.

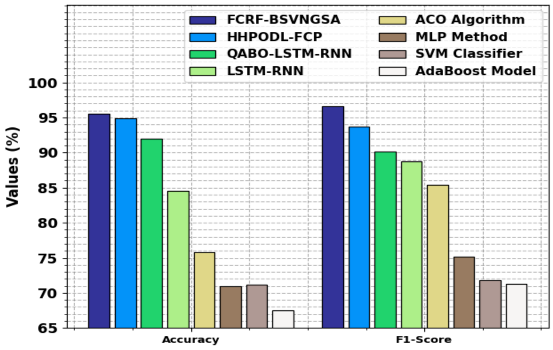

Figure 7. $Accu_y$ and $F1_{score}$ outcome of FCRF-BSVNGSA technique with existing models

5. Conclusion

In this paper, a new FCRF-BSVNGSA method is proposed. The main intention of the FCRF-BSVNGSA approach is to develop an effective method for financial credit risk prediction using advanced methods. At first, the data normalization stage applies Z-score normalization for converting input data into a beneficial format. For the financial credit risk classification process, the proposed FCRF-BSVNGSA model utilizes the BSVNG approach. Finally, the MOHO model fine-tunes the hyperparameter values of the BSVNG model optimally and results in great classification performance. An extensive simulation of the FCRF-BSVNGSA approach is performed under the Statlog (German Credit Data) dataset. The experimental validation of the FCRF-BSVNGSA approach portrayed a superior accuracy value of 95.59% over exisitng techniques. The limitations of the FCRF-BSVNGSA approach comprise the reliance on a relatively small dataset, which may not fully capture the diverse conditions or complexities of financial crises in diverse economic contexts. Moreover, the binary classification of financial crisis versus non-financial crisis may overlook more complex or intermediate categories, mitigating the capability of the model to detect subtle shifts in economic conditions. The study also does not address potential biases in the data, such as regional or sectoral disparities, which could affect the generalizability of the findings. Furthermore, the lack of real-time data integration restricts the adaptability of the model in dynamic economic environments.

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Future work may concentrate on expanding the dataset to comprise more instances from diverse economic regions and integrating multi-class classification to better capture varying crisis severity levels. Additionally, exploring hybrid approaches that incorporate real-time data with historical trends could improve the predictive capability of the model. Enhanced model interpretability and transparency should also be prioritized to enhance trust in the predictions.

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