Fuzzy Parameterized Single-Valued Neutrosophic Subset based Artificial Intelligence for Sustainable Financial Crisis Prediction and Green Finance

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Abstract

Predicting sustainable financial crises and promoting green finance are paramount in fast developing economic landscape. Leveraging advanced AI-driven technologies, such as Neutrosophic logic, enables a nuanced understanding of complex sustainability factors influencing financial markets. By incorporating these advanced technologies, organizations can proactively mitigate and identify risks related to unsustainable practices while fostering investment aligned with environmental, social, and governance (ESG) principles. This proactive stance improves financial resilience and contributes to the transition towards a resilient and more sustainable financial ecosystem. We can navigate future challenges with foresight and responsibility through the synergy of sustainable financial crisis prediction and green finance initiatives, which ensures a prosperous and environmentally conscious financial future for the generation to come. This study develops a new optimal Fuzzy Parameterized Single-Valued Neutrosophic Subset for financial crisis prediction and green finance (OFPSVNS-FCPGF) technique. The OFPSVNS-FCPGF technique intends to recognize the presence of the financial disaster in the sustainable and green finance sector. In the OFPSVNS-FCPGF technique, Z-score normalization is primarily used to measure the economic data into a beneficial layout. For the procedure of prediction, the OFPSVNS-FCPGF approach designs the FPSVNS approach which detects the occurrence of financial crises or not. Furthermore, the parameter tuning of the FPSVNS technique takes place utilizing the grasshopper optimization algorithm (GOA). To illustrate the improved FCP outcomes of the OFPSVNS-FCPGF model, a series of simulations were involved. An wide comparison study specified that the OFPSVNS-FCPGF method gains significant outcomes in the green finance sector.

Keywords: Green Finance; Financial Crisis Prediction; Grasshopper Optimization Algorithm; Neutrosophic Subset; Artificial Intelligence

1. Introduction

Green finance has become important all over the world struggling with climatic variation and ecological loss. The catastrophic effects of the modifying weather on the world and its inhabitants need immediate responses [1]. Numerous species will be destroyed because of the great increase in biodiversity loss. Several habitations and their livelihoods are also at risk of increasing sea levels. Specified the emergency condition, it is vital to consider both exploration and attention under green finance to connect its highest potential [2]. Meanwhile, financial development is an integration of diverse financial aspects and trading efficiency of corporate issues, thus, the alteration of a basic financial development system and the comprehension of green expansion as an objective, green development is a crucial organized assurance [3]. Organizations at every level must be analyzed, as the conventional enlargement system has higher per-capita resource usage and increasing ecological complexity from

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resource processing, extraction, and utilizing advanced more macroeconomic expenditures. Green evolution can disconnect financial growth from pollution and associate it with the financial and the surrounding facet [4]. Financial crisis prediction (FCP) is a main domain which supports financial organizations to create verdicts in a suitable manner for viable expansion. It is attributable to the objective of inappropriate decision-making in businesses that leads to bankruptcy or financial crises and impacts clients, vendors, stockholders, and so on [5]. The recent expansion in information technology (IT) permits achieving various categories of data related with the possibility levels of businesses from dissimilar behaviors. The majority of the individual is dependent upon the predictor's decision to evaluate a large quantity of data. However, numerous aspects may comprise an effect on performance analysis. AI and statistical methods have been implemented to identify the FCP [6]. In FCP, AI is employed for various methods. It has been employed to develop models that can be predicted once a financial organization can be affected by a crisis.

To avoid the financial risk with the minimum expenses, a precise FCP system must be required [7]. However, in the Internet world, financial information is undergoing explosive development, and combined with all categories of risk data that develops China's financial risk prevention model is complex for performance. Intended for such a large number of data, the standard processing method is time-consuming and expensive [8]. Hence, research workers in financial security offered numerous innovative financial risk prevention systems reliant on deep learning (DL) and machine learning (ML) techniques. A significant source of this study is the three features of financial data such as heterogeneity, imbalance, and multi-source that have the upcoming trends of financial data [9]. Financial information becomes more heterogeneous because there are increasingly unorganized data on the Internet like videos, images, and blogs. Indeed, the heterogeneity of financial data is frequently combined with multi-source. In the meantime, the financial data considers the nature of multi-source due to it can be obtained from various sources like an individual, organization, or even the industries [10]. Besides, the imbalance is defined as the imbalance between risky data and secure data, and the data asymmetry among stakeholders and organizations.

This study develops a new optimal Fuzzy Parameterized Single-Valued Neutrosophic Subset for financial crisis prediction and green finance (OFPSVNS-FCPGF) technique. The OFPSVNS-FCPGF technique intends to classify the presence of the financial disaster in the sustainable and green finance sector. In the OFPSVNS-FCPGF technique, Z-score normalization is primarily used to measure the economic data into a beneficial layout. For the prediction procedure, the OFPSVNS-FCPGF model designs the FPSVNS approach which detects the occurrence of financial crises or not. Furthermore, the parameter tuning of the FPSVNS technique takes place utilizing the grasshopper optimization algorithm (GOA). A wide comparison study identified that the OFPSVNS-FCPGF system gains significant outcomes in the green finance sector.

2. Literature Works

Wang [11] introduced an efficient and precise technique for analyzing the network traffic danger of a business public cloud economic model with the help of the DL method. The preprocessed data was employed for training the DL models. The network traffic risk exploration technique has been built by integrating the DL method with the model of the enterprise public cloud financial model. By employing a training DL method, the component is capable of correctly identifying abnormal behavior. Katib et al. [12] developed a hybrid hunter–prey optimizer with a DL-based FCP (HHPODL-FCP) method. Furthermore, the HHPODL-FCP algorithm utilizes the gated attention recurrent network (GARN) system. The HHPODL-FCP employs a SSA-based hyperparameter tuning method. Elhoseny et al. [13] proposed an outlier recognition system for FCP employing a political optimizer-based DNN (OD-PODNN) method. This introduced method creates usage of the isolation forest (iForest) based outlier identification system. Likewise, the PODNN-based identification method has been acquired, and DNN hyperparameters must be modified to increase the entire accuracy of classification.

Chandok et al. [14] presented an innovative white shark optimizer with DL-based bankruptcy prediction for financial risk assessment (WSODL-BPFCA) method. This technique employs a hyperparameter-tuned DL technique for predicting the presence of bankruptcy. The system also deploys min-max normalization. For bankruptcy prediction, the method presents an attention-based LSTM (ALSTM) method. In conclusion, the hyperparameter tuning of the ALSTM method has been executed by applying the WSO algorithm. Sun et al. [15] developed a MS-BGRU that combines multi-scale convolutional and dual-mode GRU. Initially, a feature extractor method was developed that integrates economic data with diverse measures by leveraging whole convolutional with different extension rates. The integrated data has been attached to get significant context data. Then, the BGRU network was utilized for distinguishing the sequence features and time data of economic indicators.

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Ramesh and Jeyakarthic, [16] considered the development of sand cat swarm optimizer-based FS with hybrid DL (SCSOFS-HDL) method. This method introduces an innovative SCSOFS method for the optimum choice of FS subsets. Moreover, the deep LSTM Supervised AE-NN (DLSTM-SANN) method was developed for categorization. To improve the efficiency, the political optimizer (PO) method was exploited for the hyperparameter tuning method. Balachander et al. [17] proposed an automatic FCP employing FS with a quantum DNN (FCPFS-QDNN) algorithm. This aims to forecast the economic crisis through the election of ML and FS methods. Primarily, the FCPFS-QDNN method standardizes the input financial information into a scalar format. And then employs ISA-FS for choosing features. In conclusion, the QDNN method was implemented for the prediction method in the financial domain.

3. The Proposed Model

In this work, we have projected an innovative OFPSVNS-FCPGF model. The OFPSVNS-FCPGF technique intends to recognize the presence of the financial disaster in the sustainable and green finance sector. It encompasses different kinds of procedures following z-score normalization, FPSVNS-based prediction process, and GOA-based parameter tuning. Fig. 1 establishes the complete method of the OFPSVNS-FCPGF technique.

A. Data Normalization

Primarily, the OFPSVNS-FCPGF technique takes place Z-score normalization used to measure the financial data into a beneficial layout. Z-score normalization, also termed standardization, is a statistical model used for rescaling the data to have a variance of one and a mean of zero [18]. This procedure includes subtracting the mean of the dataset from all the data points and later dividing by the SD. Variables are brought to a common scale by standardizing the data, which makes them directly comparable and facilitates more contextual comprehension. Z-score normalization is highly effective in statistical analysis and ML, where it helps to eradicate the effects of scale differences between variables, which ensures fair comparisons and improves the convergence and stability of the approaches.

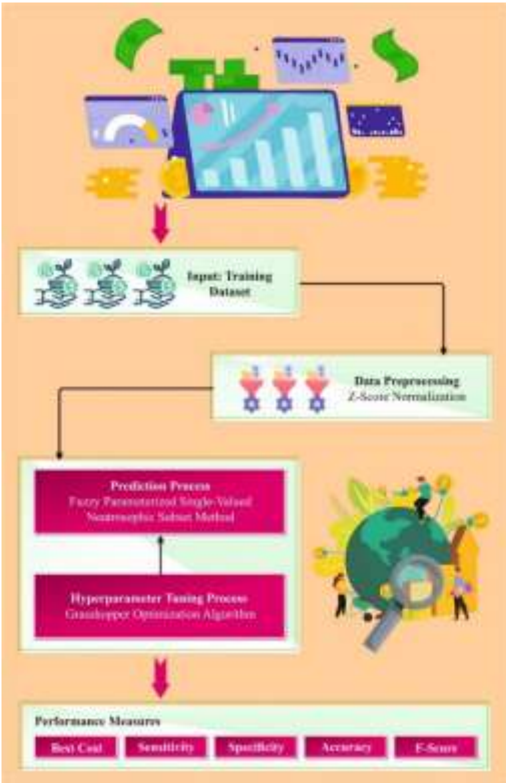

Figure 1: Overall process of OFPSVNS-FCPGF technique

B. Prediction Process using FPSVNS

For the prediction process, the OFPSVNS-FCPGF technique designs the FPSVNS approach that detects the occurrence of financial crises or not. The terms and definitions related to the main study are discussed in this section [19].

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Fuzzy set (FS) is a version of traditional set wherein a membership level is related to every components [20]. According to in traditional set, the logic dependent upon the real values like "true" and "false" in which occasionally insufficient to determine the human opinions. Alternatively, considered only two real values, fuzzy logic (FL) proceeds the total interval among 1 ('true') and 0 ('false') for superior result. A FS permits its members or components to have various membership levels at the interval [0,1]. Although FS architecture, it requires to be recognized that the description of sets differs based on the context. Consequently, the fuzzy morphological word 'tall' have one category of FS whereas defining the height of a construction and second category of FS when defining the height of humans.

Definition 1. Assume X denote the set of universal and $x \in X$, after that a FS $\hat{A}$ in X is described as $\hat{A} = \{(x, \mu_{\hat{A}}(x)) : \mu_{\hat{A}}(x) \in [0,1], x \in X\}$, the $\mu_{\hat{A}}(x)$ is known as the membership level of x in $\hat{A}$. Alternatively, $\mu_{\hat{A}}(x)$ states the level of membership of x to $\hat{A}$ or level of holding any inaccurate property characterized as $\hat{A}$.

By applying the Zadeh's min-max model, FS union, complement function, and intersection have been represented. The *union* of a 2 FSs $\hat{C}$ and $\hat{D}$ is a FS in X, indicated by $\hat{C} \cup \hat{D}$, the membership level will be given $\mu_{\hat{C}\cup\hat{D}} = \mu_{\hat{C}}(x) \vee \mu_{\hat{D}}(x) = \max\{\mu_{\hat{C}}(x), \mu_{\hat{D}}(x)\}$ for each $x \in X$.

$$\hat{C} \cup \hat{D} = \{(x, \mu_{\hat{C}\cup\hat{D}}(x)) : \mu_{\hat{C}\cup\hat{D}}(x) = \max\{\mu_{\hat{C}}(x), \mu_{\hat{D}}(x)\}, \forall x \in X\}.$$

Neutrosophic FS and the application for taking decision

The *intersection* of $\hat{C}$ and $\hat{D}$ is a FS at X, represented by $\hat{C} \cap \hat{D}$, which membership level will be $\mu_{\hat{C}\cap\hat{D}} = \mu_{\hat{C}}(x) \wedge \mu_{\hat{D}}(x) = \max\{\mu_{\hat{C}}(x), \mu_{\hat{D}}(x)\}$ for each $x \in X$. So

$$\hat{C} \cap \hat{D} = \{(x, \mu_{\hat{C}\cap\hat{D}}(x)) : \mu_{\hat{C}\cap\hat{D}}(x) = \max\{\mu_{\hat{C}}(x), \mu_{\hat{D}}(x)\}, \forall x \in X\}.$$

Consider $\hat{D}$ is a FS determining over X. After its complement, $\hat{D}^c$, will be denoted with respect of membership degree as $\mu_{\hat{D}^c}(x) = 1 - \mu_{\hat{D}}(x)$ for each $x \in X$.

$$\hat{D}^c = \{(x, \mu_{\hat{D}^c}(x)) : x \in X, \mu_{\hat{D}^c}(x) = 1 - \mu_{\hat{D}}(x)\}$$

This section presents the Neutrosophic fuzzy set (NFS) in which the fuzzy membership degree of all components are related to neutrosophic elements namely falsity, truth, and indeterminacy membership levels. The combination of neutrosophic constituents to FS is required for controlling the real time data that have both unreliable and unpredictable naturally. In diverse real time issues, the membership level of a FS could not be entirely ensured because of the inaccurate and unreliable features of human excellence. Hence, it is further sensible to include neutrosophic elements to choose the level of membership. According to this standpoint, the authors develop the NFS. Otherwise stated, the membership level of the neutrosophic elements will be represented with NFS.

Definition 6. Consider Y is an objects set and $\hat{A} = \{(y, \mu_{\hat{A}}(y)), \mu_{\hat{A}}(y) \in [0,1], y \in Y\}$ be a FS. Next, a NFS A in Y could be determined by $A = \{y, \mu_A(y), T_A(y,\mu), I_A(y,\mu), F_A(y,\mu)\}, y \in Y$, every membership value can be denoted by a falsity, indeterminacy, and truth membership operation that have been correspondingly signified as $T_A(y,\mu)$, $I_A(y,\mu)$, and $F_A(y,\mu)$. Additionally T_A, I_A and F_A have the real standard or non-standard subsets of $]0^-$, $1^+[$ $T_A: Y \rightarrow]0^-, 1^+[$, $I_A: Y \rightarrow]0^-, 1^+[$, and $F_A: Y \rightarrow]0^-, 1^+[$. Without limitation, the sum of T_A, I_A, and F_A. Hence, $0^- \leq sup T_A + \sup I_A + \sup F_A \leq 3^+$. In order to a fixed $\in Y$, $\{\mu_A(y), T_A(y), I_A(y), F_A(y)\}$, i.e., in simple form, $\{\mu_A, T_A, I_A, F_A\}$ is known as neutrosophic fuzzy number (NFN).

Meanwhile T_A, I_A and F_A describes true non-standard and standard subsets of $]0^-, 1^+[$, it is hard to implement NFS in engineering and scientific uses. It provides the single valued NFS (SVNFS) as more discussed.

Now we develop the concept of SVNFS as a sample of NFS to utilize in real time applications.

Definition 7 Assume Y is an object set of and $\hat{S} = \{(y, \mu_{\hat{S}}(y)), \mu_{\hat{S}}(y) \in [0,1], y \in Y\}$ be a FS. Next, a SVNFS S in Y can be stated by $S = \{y, \mu_S(y), T_S(y,\mu), I_S(y,\mu), F_S(y,\mu)\}, y \in Y$, whereas $T_S(y,\mu)$, $I_S(y,\mu)$, $F_S(y,\mu) \in [0,1]$ and $0 \leq T_S(y,\mu) + I_S(y,\mu) + F_S(y,\mu) \leq 3$.

For instance 1 Assume $Y = \{y_1, y, y_3\} = \{\text{brand name, volume, price}\}$ have a 3 parameters that financiers utilize in stock market. These parameter have been characterized by a grade of "bad profit" and "good profit" that have been introduced by falsity, indeterminacy, and truth membership operation, where the "profit" performs the fuzzy membership operation. The A and B describes two investors that will be denoted by SVNFSs of Y, then A and B are described as

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$A = \{y_1, 0.8,0.7,0.2,0.2\}, \{y_2, 0.4,0.5,0.6,0.4\}, \ \{y_3, 0.6,0.4,0.8,0.5\}$

$B = \{y_1, 0.7,0.4,0.8,0.2\}, \{y_2, 0.8,0.9,0.0,0.1\}, \{y_3, 0.3,0.5,0.3,0.7\}$

Now, the three parameter of investors namely cost, volume, and brand name have been represented employing NFN. In SVNFS A, for the parameter y_1, the NFN is $\{0.8,0.7,0.2,0.2\}$, where 0.2 denotes the unspecified membership, 0.7 is the real membership, 0.2 represents the falsity membership values, and 0.8 is the fuzzy membership level.

Definition2.1

A single value neutrosophic subset M on $\aleph$ is expressed as $= \{\chi, (|T_{M(\chi)}, I_{M(\chi)}, F_{M(\chi)}) : \chi \in E, |T_M, I_M, F_M \in [0,1]$ where the membership, indeterminacy, and non-membership functions were represented as T_M, I_M, F_M, correspondingly, and $0 \leq |T_{M(\chi)} + I_{M(\chi)} + F_{M(\chi)}| \leq 3$.

Definition2.2

Consider the set of parameters as ∇, and U denotes the universe with power set $P(U)$. $T = \{\alpha^{f(\alpha):\alpha\in\nabla}\}$ shows the set of fuzzy, $h: \nabla \to Y = [0,1]$, and $h(\alpha) = \{\eta^{\mu(\alpha),v(\alpha)}: \alpha \in \nabla\}$ indicates the intuitionistic fuzzy set over U. The pair of intuitionistic fuzzy soft has been formulated as $= \{\ (\alpha^{f(\alpha)}, h(\alpha): \alpha \in \nabla)\}$, whereas $h(a)$ shows the estimated R function.

Definition2.3

A FPIFS-set $\check{C}$ is assumed an alternative FPIFS-set $\widetilde{N}$ when $h_1(a) \subseteq h_2(a)$ and $f_1(a) \leq f_2(a)$ for $a \in \nabla$.

Definition2.4

A set of FPIFS $\check{C}$ is equivalent to $\widetilde{N}$ if $h_1(a) = h(a)$ and $f_1(a) = f(a)$ for $a \in \nabla$.

Definition2.5

The union of $\check{C}$ and $\widetilde{N}$ is represented as $\check{C} \cup \widetilde{N} = \{(b^{\max\{f1(a), f1(a)\}}, h_1(a) \cup h_2(a))\}$.

Definition2.6

The inter-section of $\check{C}$ and $\widetilde{N}$ is given by: $\check{C} \cap \widetilde{N} = \{(b^{\min\{f1(a), f1(a)\}}, h_1(a) \cap h_2(a))\}$.

The making of decision process concentrating on multiple feature which was applied for the assortment method.

Definition3.1

The FPIFS is expressed as a pair $(F, \nabla)_\Omega$ over U, where the mapping F_Ω is referred to as $F_{\Omega:}\nabla \to N$ and $N(U)$ denotes the pair of single-value neutrosophic sub-sets of U. Assume $U = \{O_1, O_2\}$ as a pair of construction concerns, and the group of different attributes as $\{< \Gamma_1 =$cbeap, $\Gamma_2 =$normal, $\Gamma_3 =$superior service, $\Gamma_4 =$excellence, $\Gamma_5 = location\}$. Assume $\{< \Gamma_1/0.2, \Gamma_2/0.3, \Gamma_3/0.4, \Gamma_4/0.5, \Gamma_5/0.6\}$ as the group of fuzzy I^U.

$$F(\Gamma_1/0.2) = \{O_1/< 0.2,0.3,0.4 >, O_2/< 0.1,0.5,0.4 >\},$$

$$F(\Gamma_2/0.3) = \{O_1/< 0.1,0.3,0.7 >, O_2/< 0.1,0.6,0.4 >\},$$

$$F(\Gamma_3/0.4) = \{O_1/< 0.4,0.1,0.5 >, O_2/< 0.3,0.2,0.8 >\},$$

$$F(\Gamma_4/0.5) = \{O_1/< 0.5,0.6,0.8 >, O_2/< 0.3,0.8,0.9 >\},$$

$$F(\Gamma_5/0.6) = \{O_1/< 0.9,0.3,0.6 >, O_2/< 0.5,0.5,0.4 >\}.$$

The FPIFS is formulated by:

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$$(S,U)=\left\{\begin{matrix}\left((\Gamma_1/0.2), & \left\{\frac{O_1}{\langle 0.2,0.3,0.4\rangle},\frac{O_2}{\langle 0.1,0.4,0.5\rangle},\right\}\right)\\ \left((\Gamma_2/0.3), & \left\{\frac{O_1}{\langle 0.1,0.3,0.7\rangle},\frac{O_2}{\langle 0.1,0.6,0.4\rangle},\right\}\right)\\ \left((\Gamma_3/0.4), & \left\{\frac{O_1}{\langle 0.4,0.1,0.5\rangle},\frac{O_2}{\langle 0.3,0.2,0.8\rangle},\right\}\right)\\ \left((\Gamma_4/0.5), & \left\{\frac{O_1}{\langle 0.5,0.6,0.8\rangle},\frac{O_2}{\langle 0.3,0.8,0.9\rangle},\right\}\right)\\ \left((\Gamma_5/0.6), & \left\{\frac{O_1}{\langle 0.9,0.3,0.6\rangle},\frac{O_2}{\langle 0.5,0.4,0.4\rangle},\right\}\right)\end{matrix}\right\}. \quad (1)$$

Definition3.2

A FPIFS(S,W) is a subset of alternative FPIFS (R,Y) if (i) W is a sub-set of Y, and (ii) $S(d)$ is a solitary-value set of neutrosophic of $Y(d)$ for d in S.

Definition3.3

$ç'(S(\beta))$ is the complement of FPIFS $(S,W)^C$ for β belongs to U, where $ç'$ indicates the single-valued neutrosophic complement.

$$(S,U)^c=\left\{\begin{matrix}\left((\Gamma_1/0.2), & \left\{\frac{O_1}{\langle 0.4,0.7,0.2\rangle},\frac{O_2}{\langle 0.9,0.6,0.5\rangle},\right\}\right)\\ \left((\Gamma_2/0.3), & \left\{\frac{O_1}{\langle 0.7,0.7,0.3\rangle},\frac{O_2}{\langle 0.4,0.4,0.1\rangle},\right\}\right)\\ \left((\Gamma_3/0.4), & \left\{\frac{O_1}{\langle 0.5,0.9,0.4\rangle},\frac{O_2}{\langle 0.8,0.8,0.3\rangle},\right\}\right)\\ \left((\Gamma_4/0.5), & \left\{\frac{O_1}{\langle 0.8,0.4,0.5\rangle},\frac{O_2}{\langle 0.9,0.2,0.3\rangle},\right\}\right)\end{matrix}\right\}. \quad (2)$$

Definition3.4

The union of (S,W) and (R,Y) is given as: $u(S(\beta),R(\beta))=\{<\alpha,\ \max\{p_1(\beta),p_2(\beta)\},\ \min\{q_1(\beta),q_2(\beta)\},\ \min\{r_1(\beta),r_2(\beta)\}>\}$.

$$(S,A)=\left\{\begin{matrix}\left((\Gamma_1/0.2), & \left\{\frac{O_1}{\langle 0.2,0.3,0.4\rangle},\frac{O_2}{\langle 0.1,0.4,0.5\rangle},\right\}\right)\\ \left((\Gamma_2/0.3), & \left\{\frac{O_1}{\langle 0.1,0.3,0.7\rangle},\frac{O_2}{\langle 0.1,0.6,0.4\rangle},\right\}\right)\\ \left((\Gamma_3/0.4), & \left\{\frac{O_1}{\langle 0.4,0.1,0.5\rangle},\frac{O_2}{\langle 0.3,0.2,0.8\rangle},\right\}\right)\end{matrix}\right\} \quad (3)$$

$$(U,B)=\left\{\begin{matrix}\left((\Gamma_1/0.2), & \left\{\frac{O_1}{\langle 0.1,0.3,0.2\rangle},\frac{O_2}{\langle 0.1,0.6,0.5\rangle},\right\}\right)\\ \left((\Gamma_2/0.3), & \left\{\frac{O_1}{\langle 0.1,0.3,0.9\rangle},\frac{O_2}{\langle 0.1,0.3,0.4\rangle},\right\}\right)\end{matrix}\right\}. \quad (4)$$

The union of FPSVN-sets is computed by:

$$(V,C)=\left\{\begin{matrix}\left((\Gamma_1/0.2), & \left\{\frac{O_1}{\langle 0.2,0.3,0.2\rangle},\frac{O_2}{\langle 0.1,0.4,0.5\rangle},\right\}\right)\\ \left((\Gamma_2/0.3), & \left\{\frac{O_1}{\langle 0.1,0.3,0.7\rangle},\frac{O_2}{\langle 0.1,0.3,0.4\rangle},\right\}\right)\\ \left((\Gamma_3/0.4), & \left\{\frac{O_1}{\langle 0.4,0.1,0.5\rangle},\frac{O_2}{\langle 0.3,0.2,0.8\rangle},\right\}\right)\end{matrix}\right\}. \quad (5)$$

Definition3.5

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The inter-section of (S, W) and (R, Y) is given as: $u(S(\beta), R(\beta)) = \{< a, \min\{p_1(\beta), p_2(\beta)\}, \max\{q_1(\beta), q_2(\beta)\}, \max\{r_1(\beta), r_2(\beta)\} >\}$.

$$(S, A) = \begin{Bmatrix} \left((\Gamma_1/0.2), \quad \left\{\frac{O_1}{\langle 0.2,0.3,0.4\rangle}, \frac{O_2}{\langle 0.1,0.4,0.5\rangle}, \right\}\right) \\ \left((\Gamma_2/0.3), \quad \left\{\frac{O_1}{\langle 0.1,0.3,0.7\rangle}, \frac{O_2}{\langle 0.1,0.6,0.4\rangle}, \right\}\right) \\ \left((\Gamma_3/0.4), \quad \left\{\frac{O_1}{\langle 0.4,0.1,0.5\rangle}, \frac{O_2}{\langle 0.3,0.2,0.8\rangle}, \right\}\right) \end{Bmatrix} \tag{6}$$

$$(U, B) = \begin{Bmatrix} \left((\Gamma_1/0.2), \quad \left\{\frac{O_1}{\langle 0.1,0.3,0.2\rangle}, \frac{O_2}{\langle 0.1,0.6,0.5\rangle}, \right\}\right) \\ \left((\Gamma_2/0.3), \quad \left\{\frac{O_1}{\langle 0.1,0.3,0.9\rangle}, \frac{O_2}{\langle 0.1,0.3,0.4\rangle}, \right\}\right) \end{Bmatrix}. \tag{7}$$

The inter-section of the FSVN set is represented by:

$$(V, C) = \begin{Bmatrix} \left((\Gamma_1/0.2), \quad \left\{\frac{O_1}{\langle 0.1,0.3,0.4\rangle}, \frac{O_2}{\langle 0.1,0.6,0.5\rangle}, \right\}\right) \\ \left((\Gamma_2/0.3), \quad \left\{\frac{O_1}{\langle 0.1,0.3,0.9\rangle}, \frac{O_2}{\langle 0.1,0.6,0.4\rangle}, \right\}\right) \end{Bmatrix}. \tag{8}$$

C. Hyperparameter Tuning using GOA

Finally, the parameter tuning of the FPSVNS technique takes place utilizing the GOA. Metaheuristic approaches are based on simulating nature [21]. Universal optimizer problems are classically resolved utilizing these approaches. Distinct types of metaheuristic approaches contain those that depend on evolution, physical and chemical, SI, and human-based processes. It is optimized utilizing GOA in this work. The effective metaheuristic approach GOA utilizes optimizer relies on a swarm that is simulated by natural procedures. According to this case, GOA has been employed to define the input variable ideal values (ideal factor rates). The optimizer procedure is then executed to GOA utilizing these approaches. GOA simulates the organic approaches of grasshopper swarms. These 2 phases of nature-inspired optimizer systems are exploration and exploitation. An immediate movement throughout the exploration is developed by the searching agents of the optimizer approach. But it can be migrated more locally throughout exploitation.

$$X_i = r_1 S_i + r_2 G_i + r_3 A_i \tag{9}$$

During this formula, i signifies all the grasshoppers and X_i represents the i_{th} grasshopper is placed. S_i refers to the grasshoppers connect. Also, G_i and A_i implies the gravity power and wind advection. The random numbers within the interval of zero and one are the r variables. Eq. (2) offers data on grasshopper social manner (attraction-repulsion):

$$S_i = \sum_{\substack{j=1 \\ j\neq 1}}^{N} s(d_{ij})\widehat{d_{ij}} \tag{10}$$

According to this formula, s represents the strength of social forces $\left(s_r = f e^{-\frac{r}{l}} - e^{-r}\right)$, l signifies the seductive range scale, and f for attraction power. N illustrates the grasshopper number A vector amongst 2 grasshoppers is named as d_{ij} $\left(d_{ij} = |x_j - x_i|\right)$, and $\widehat{d_{ij}}$ refers to the exact range of the $i^{th}$and j^{th} grasshoppers $(\widehat{d_{ij}} = (x_j - x_i)/d_{ij})$. Artificial grasshopper social connections have been controlled by s function. This function separates the interval among both grasshoppers into 3 pieces (comfort, attraction, and repulsion regions). The safe region could not but attraction and repulsion operate. This region can be modified by f and l. But, the s function turns to 0 when this range exceeds 10. Accordingly, this function could not create influential pressures throughout the long-range among grasshoppers. Other elements of X_i is G_i (gravitational power):

$$G_i = -g\widehat{e_g} \tag{11}$$

In Eq. (11), g signifies the gravity constant and $\widehat{e_g}$ for unity vector pointing near the center of the earth. The final element of X_i is A_i (wind advection):

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$$A_i = u\widehat{e_w} \tag{12}$$

Based on this formula, $\widehat{e_w}$ and u signifies the unity vector and constant drift from the wind direction. Typical swarm-based approaches simulate the swarm while it searches and utilizes the searching region all over performances. The GOA technique of X_i replicates the connections of a swarm of grasshoppers but the mathematical expressions are in free region. It simulates that grasshoppers can perform in several spatial dimensional, comprising 2D, 3D, and hyper-dimensional regions.

$$X_i^d = c\left(\sum_{\substack{j=1,\\ j\neq 1}}^{N} c\frac{ub_d - lb_d}{2} s\left(x_j^d - x_i^d\right)\frac{x_j - x_i}{d_{ij}}\right) + \widehat{T_d} \tag{13}$$

The low and up bounds within the D_{th} dimensional s_r are named as lb_d and ub_d. The comfort, repulsion, and attraction regions can be decreased by the lower co-efficient c that creates $\widehat{T_d}$ the optimum (target) solution. All the search units in GOA have one location vector that computes each search unit following place. Eq. (13) initial stage, the summation, replicates the grasshopper connection by assuming the places of many grasshoppers. T_d reflects their propensity to move in the direction of food resources. Finally, c imitates the grasshopper delay but it obtains the food resource in Eq. (14).

$$c = c\max - l\frac{c\max - c\min}{L} \tag{14}$$

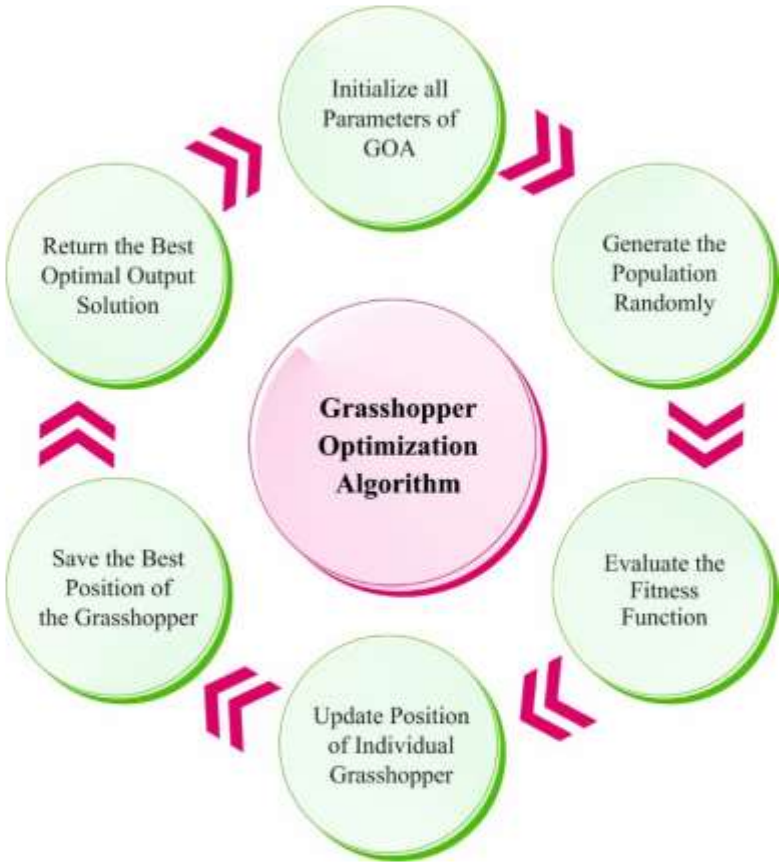

Figure 2: Flowchart of GOA

During this formula, the existing iteration and the iteration maximum number L and l. The minimal and maximal values have been represented by $cmin$ and $cmax$. It can be employed the similar settings employed $cmax = 1$ and $= 0.00001$. In summary, the swarm final methods have a set goal as the safe region has been decreased by c variable. The swarm effectively tracks a moving goal by $\widehat{T_d}$. The grasshoppers will reach the objective through numerous iterations. Fig. 2 represents the flowchart of GOA.

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The GOA derives a fitness function (FF) to achieve superior performance of classificer. It defines a positive number to signify the higher performance of the candidate solution. In this work, the classificer error rate minimizer is reflected as FF that assumed in Eq. (15).

$$fitness(x_i) = ClassifierErrorRate(x_i) = \frac{no.of\ misclassified\ intances}{Total\ no.of\ instances} * 100 \qquad (15)$$

4. Result Analysis and Discussion

In this section, the performance evaluation of the OFPSVNS-FCPGF model is verified using the German Credit [22] and Australian Credit [23]. The German Credit database includes 1000 samples and the Australian Credit database comprising 690 samples as defined in Table 1. The OFPSVNS-FCPGF technique has chosen 15 and 8 features under Australian Credit and German Credit database.

Table 1: Details on database

Database	# of instances	# of attributes	# of class	Financial Crisis/ Non-Financial Crisis
German Credit	1000	24	2	300/700
Australian Credit	690	14	2	383/307

In Fig. 3, the comparative FS outcomes of the OFPSVNS-FCPGF technique with other FS techniques under German Credit database. The results indicate that the OFPSVNS-FCPGF technique has shown better performance with least best cost (BC) of 0.104. At the same time, the HHPODL-FCP, QABO-FS, ACO-FS, and GWO-FS models have got poor performance with BC of 0.117, 0.140, 0.146, and 0.158, respectively. In Fig. 4, the comparative FS outcomes of the OFPSVNS-FCPGF model with other FS systems below Australian Credit database. The results state that the OFPSVNS-FCPGF approach has shown enhanced performance with least BC of 0.028. Simultaneously, the HHPODL-FCP, QABO-FS, ACO-FS, and GWO-FS approaches have achieved poor performance with finest cost of 0.041, 0.051, 0.076, and 0.090, respectively.

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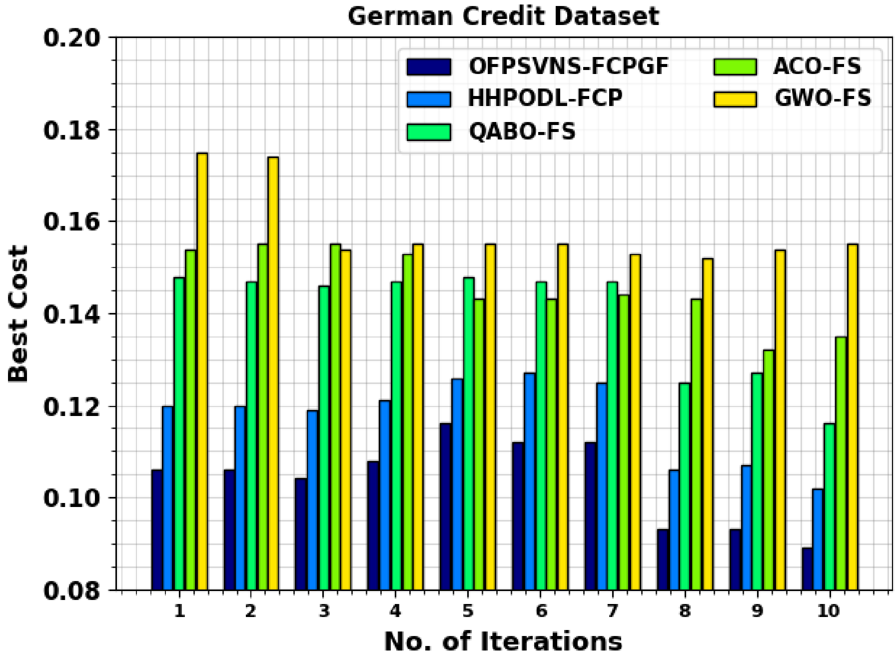

Figure 3: BC analysis of OFPSVNS-FCPGF technique under German Credit database

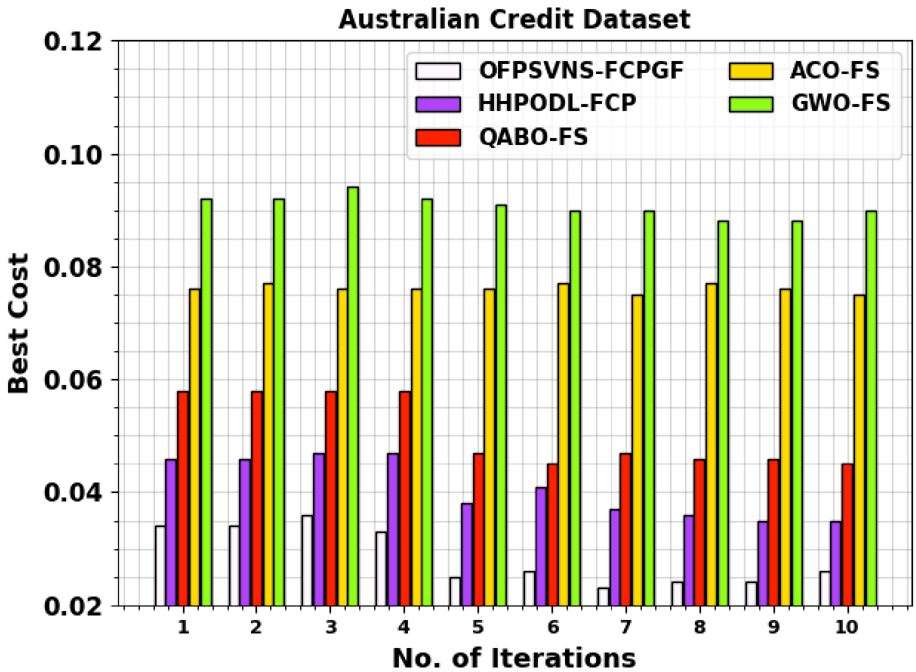

Figure 4: BC analysis of OFPSVNS-FCPGF model under Australian Credit database

The performance of the OFPSVNS-FCPGF technique is graphically offered in Fig. 5 in the method of training accuracy (TRAA) and validation accuracy (VALA) curves below German Credit database. The figure display beneficial clarification into the behaviour of the OFPSVNS-FCPGF technique over numerous epoch count, representing its learning procedure and generalization skills. Remarkably, the figure conclude a steady improvement in the TRAA and VALA with a development in epochs. It certifies the adaptive nature of the OFPSVNS-FCPGF technique in the pattern detection procedure on both TR and TS data. The arising trend in VALA plans the ability of the OFPSVNS-FCPGF technique on familiarizing to the TR data and also shining in offering precise classification on hidden data, indicating out the strong generalization skills.

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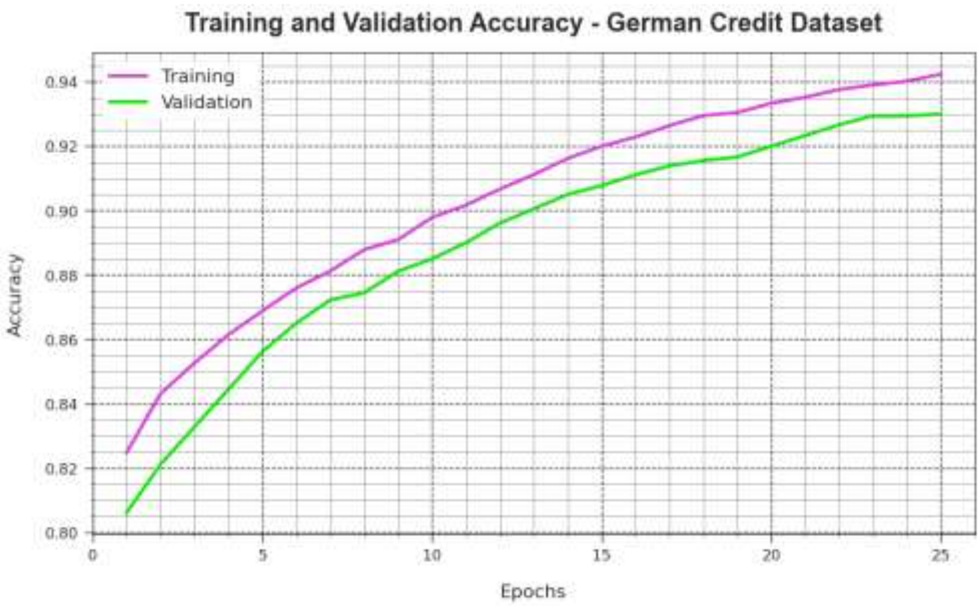

Figure 5: $Accu_y$ curve of OFPSVNS-FCPGF technique under German Credit database

Fig. 6 reveals a comprehensive representation of the training loss (TRLA) and validation loss (VALL) results of the OFPSVNS-FCPGF system over different epochs under German Credit database. The advanced reduction in TRLA highlights the OFPSVNS-FCPGF method enhancing the weights and diminishing the classification error on the TR and TS data. The figure specify a clean understanding into the OFPSVNS-FCPGF model's association with the TR data, underlining its ability in taking patterns within both databases. Remarkably, the OFPSVNS-FCPGF system repeatedly enhances its parameters in decreasing the changes between the forecast and actual TR class labels.

Figure 6: Loss curve of OFPSVNS-FCPGF technique under German Credit database

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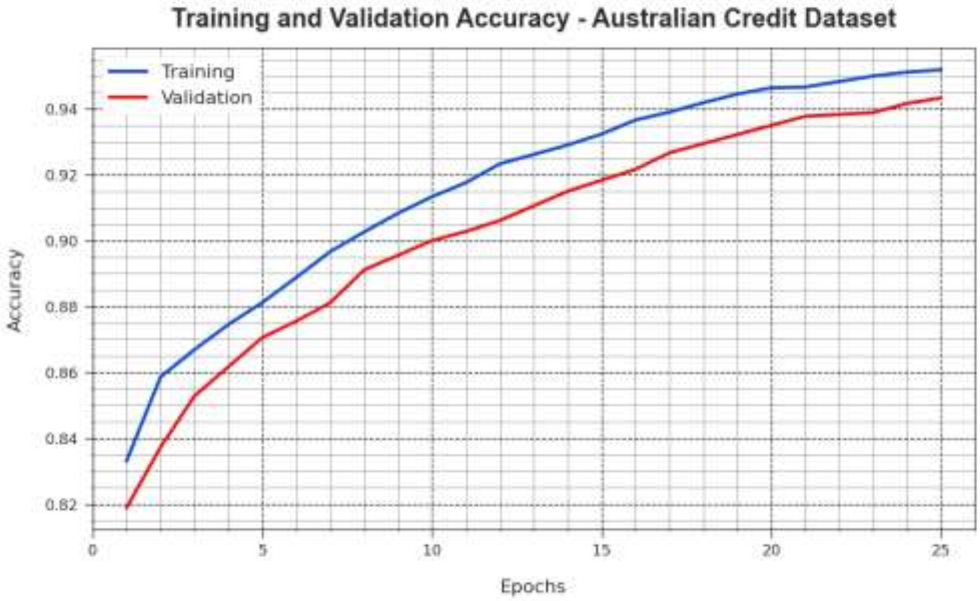

Figure 7: $Accu_y$ curve of OFPSVNS-FCPGF technique under Australian Credit database

The performance of the OFPSVNS-FCPGF technique is graphically presented in Fig. 7 in the method of TRAA and VALA curves below Australian Credit database. The figure display beneficial interpretation into the behaviour of the OFPSVNS-FCPGF system over numerous epoch count, representing its learning procedure and generalization abilities. Remarkably, the figure conclude a stable improvement in the TRAA and VALA with an improvement in epochs. It certifies the adaptive nature of the OFPSVNS-FCPGF approach in the pattern detection procedure on both TR and TS data. The arising trend in VALA outlines the ability of the OFPSVNS-FCPGF technique on adjusting to the TR data and shining in proposing correct classification on unseen data, indicating out the robust generalization abilities.

Fig. 8 demonstrates a thorough representation of the TRLA and VALL outcomes of the OFPSVNS-FCPGF technique over diverse epochs under Australian Credit database. The progressive reduction in TRLA highlights the OFPSVNS-FCPGF system enhancing the weights and reducing the classification error on the TR and TS data. The figure specify a clean understanding into the OFPSVNS-FCPGF model's link with the TR data, highlighting its skill in capturing patterns within both databases. Remarkably, the OFPSVNS-FCPGF method repeatedly increases its parameters in decreasing the differences between the forecast and actual TR class labels.

Figure 8: Loss curve of OFPSVNS-FCPGF technique under Australian Credit database

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Fig. 9 reports a comprehensive comparison study of the OFPSVNS-FCPGF technique on the German Credit database. The results indicate that the ACO, MLP, SVM, and AdaBoost models have shown worst performance. Along with that, the QABO-LSTM-RNN and LSTM-RNN models have gained slightly boosted results. Meanwhile, the HHPODL-FCP model has reported reasonable performance. However, the OFPSVNS-FCPGF technique indicates superior performance with maximum $sens_y$, $spec_y$, $accu_y$, and F_{score} of 95.12%, 95.71%, 96.58%, and 95.30%, correspondingly.

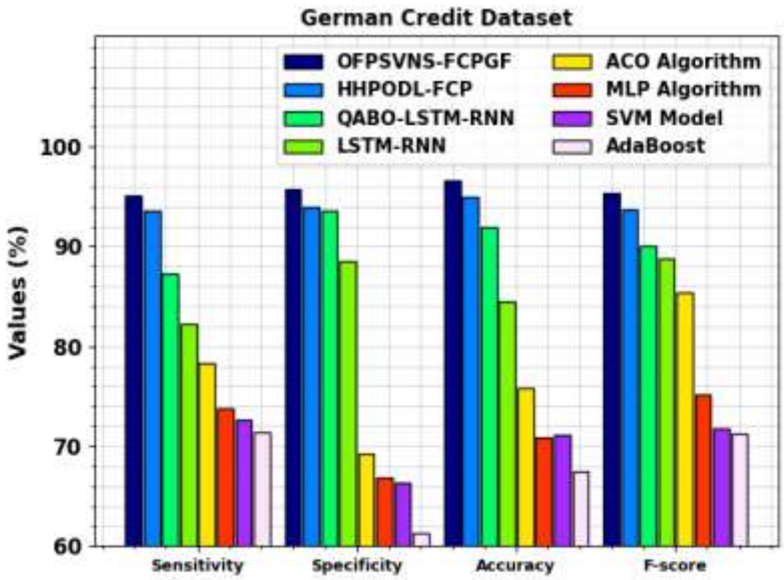

Figure 9: Comparative analysis of OFPSVNS-FCPGF system under German Credit database

Fig. 10 reports a detailed comparison study of the OFPSVNS-FCPGF approach on the Australian Credit database. The outcomes specify that the ACO, MLP, SVM, and AdaBoost approaches have shown poor performance. Beside with that, the QABO-LSTM-RNN and LSTM-RNN techniques have attained slightly increased consequences. In the meantime, the HHPODL-FCP approach has conveyed reasonable performance. However, the OFPSVNS-FCPGF system indicates greater performance with highest $sens_y$, $spec_y$, $accu_y$, and F_{score} of 95.89%, 96.16%, 96.64%, and 96.45%, respectively. Thus, the OFPSVNS-FCPGF method can be functional for boosted FCP procedure.

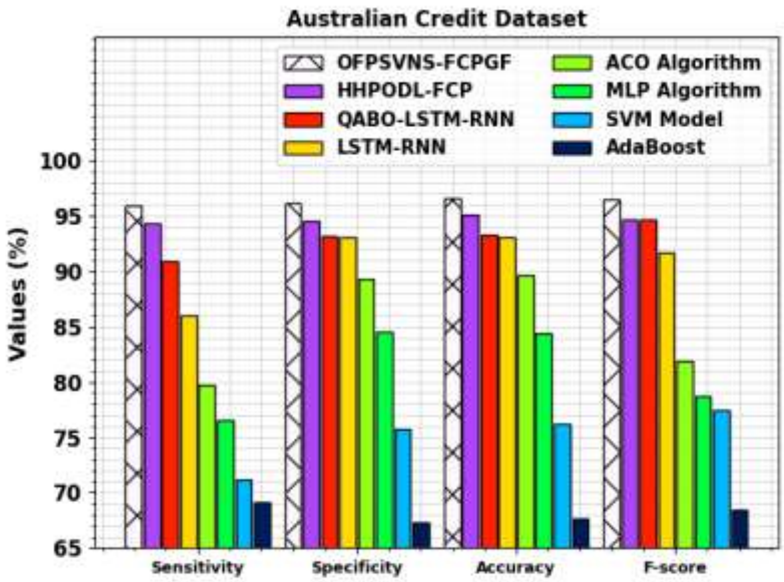

Figure 10: Comparative analysis of OFPSVNS-FCPGF model under Australian Credit database

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6. Conclusion

In this research paper, we have established an innovative OFPSVNS-FCPGF model. The OFPSVNS-FCPGF technique intends to categorize the presence of the financial disaster in the sustainable and green finance sector. It encompasses different kinds of procedures following z-score normalization, FPSVNS-based prediction process, and GOA-based parameter tuning. Primarily, the OFPSVNS-FCPGF technique takes place Z-score normalization used to measure the financial data into a beneficial layout. For the prediction process, the OFPSVNS-FCPGF technique designs the FPSVNS approach that detects the occurrence of financial crises or not. In addition, the parameter tuning of the FPSVNS technique takes place utilizing the GOA. To demonstrate the improved FCP results of the OFPSVNS-FCPGF system, a series of simulations were involved. A wide comparison study indicated that the OFPSVNS-FCPGF approach gains significant outcomes in the green finance sector.

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