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An Intelligent Financial Risk Management System Using Pythagorean Neutrosophic Fuzzy Graphs with Growth Optimization Algorithm

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Abstract

One of the most effective devices to model uncertainty in decision-making difficulties is the neutrosophic set (NS) and its extensions, namely interval NS (INS), interval complex NS (ICNS), and complex NS (CNS). An effective device to demonstrate ambiguities and uncertainty in decision-making is the NS, which is the more conventional standard set, intuitionistic fuzzy set (IFS), and fuzzy set (FS) by including 3 scores of falsehood, indeterminacy, and truth of established statements. Financial risk management is a massive field with different and developing modules, as demonstrated by either its historic growth or present classic example. It is a procedure to address the uncertainty originating from financial markets. It consists of calculating the financial threats dealing with organization and emerging management tactics by internal policies and priorities. A risk-management method is an experience control and accounting system. In this manuscript, we develop an Intelligent Risk Management Approach for Financial Crisis Using Pythagorean Neutrosophic Fuzzy Graphs and Metaheuristic Optimization Algorithms (IRMFC-PNFGMOA). The main intention of IRMFC-PNFGMOA technique is to analyse and develop effective methodologies for measuring and managing financial risk in dynamic market conditions. Initially, the data pre-processing stage applies Z-score normalization to clean, transform, and structure raw data to improve the quality. Besides, the Aquila optimization algorithm (AOA) has been deployed for the selection of feature processes to identify and retain the most relevant features from input data. For the classification process, the proposed IRMFC-PNFGMOA model designs pythagorean neutrosophic fuzzy graphs (PNFG) technique. To further optimize model performance, the growth optimizer (GO) algorithm is utilized for hyperparameter tuning to ensure that the best hyperparameters are selected for enhanced accuracy. To exhibit the enhanced performance of the presented IRMFC-PNFGMOA model, a comprehensive experimental analysis is made. The comparative results reported the improvised characteristics of the IRMFC-PNFGMOA model.

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1. Introduction of Financial Risk Management

Neutrosophic Logic is a new research field where every proportion is anticipated for the proportion of indeterminacy in subset I, the proportion of falsity in a subset F, and the proportion of truth in a subset T [1]. Neutrosophic set (NS) was successfully employed for uncertain processing of information, and exhibits benefit for dealing with the information indeterminacy of the data and it is still a model sponsored for analysis of data and application classifications [2]. NS offers a precise and effective way of defining uneven information based on the data attributes.

At present, financial risk has risen significantly, where risk and managing risk are not modern problems [3]. The consequence of increasing the world market is where the hazard might be created by even a thousand miles away that have nothing to do with the national markets [4]. Data is accessible immediately that states the changes, and consequent reactions of the market, which occurs rapidly. The financial markets and climate may be affected rapidly by the fluctuations in interest rates, commodity prices and exchange rates. Counterparties will quickly turn problematic [5]. As an effect, it is significant to safeguard financial risks that are managed and identified properly. Financial risk management is a procedure for dealing with the uncertainty, which results from the financial markets [6]. It includes evaluating the financial risks faced by the business and developing management tactics reliable with internal policies and priorities. Addressing financial risk actively can provide the organization with comparative advantages also it safeguards management, stakeholders, the board of directors, and operational staff are in contact with the main risk issues. Business manages financial risk utilizing various products and tactics. It is significant to know in what way this strategy and products are working in reducing hazards in the setting of the business's objectives and risk tolerances [7].

A risk-management system is a control and exposure accounting method. An exposure accounting method is a dynamic system that allows managers to measure the cause of variations in the aspects of economics like yield-curve shifts and reshaping, stock price movements, commodity price moves and currency, and interest-rate movements in the economic loss and profit of the business [8]. It controls the company's requirement for funds to help its position. In previous years, value-at-risk (VAR) became an accepted rule in the financial industries. It creates the foundation to determine a bank's governing funds for market risk. Several financial institutions utilize VAR as a dynamic risk measure, and VAR is frequently revealed to depositors [9]. These techniques of exposure accounting assume that the upcoming activities in risk aspects are parallel to previous activities. The VAR assess is a probability-based assessment of potential loss, assessed through a unified maintaining time and to a unified degree of arithmetical assurance [10].

This study developed an Intelligent Risk Management Approach for Financial Crisis Using Pythagorean Neutrosophic Fuzzy Graphs and Metaheuristic Optimization Algorithms (IRMFC-PNFGMOA). Primarily, the data pre-processing phase utilizes Z-score normalization. Moreover, the Aquila optimization algorithm (AOA) has been used for the feature selection process. The pythagorean neutrosophic fuzzy graphs (PNFG) technique is applied in the classification process. To additionally improve model performance, the growth optimizer (GO) algorithm is applied for hyperparameter tuning to guarantee that the best hyperparameters are selected for improved accuracy. The comparative results reported the improvised characteristics of the IRMFC-PNFGMOA model.

2. Financial Crisis Literature Review

Cheng et al. [11] introduced a DL method that depends on the union of bidirectional long short-term memory network (BiLSTM) and convolutional neural network (CNN) for discriminatory analysis of systemic financial risk. This technique initially used CNN for extracting local designs of multi-dimensional characteristics of the financial market. The bidirectional dependence of time-series by BiLSTM widely describes the varying systemic risk laws in temporal dynamics and spatial features. In [12], the DL technique, together with Gated Recurrent Unit (GRU) joint with attention mechanisms was employed to improve the possibility of recognizing and assessing risk precision of irregular transaction behavior in financial market. The GRU efficiently resolves the gradient vanishing problems in classical re-current neural networks by its singular gated design, permitting the method for learning more secure and efficient representation of features in long-series data. In the manner, the contextual attention (CA) model in the attention mechanism was presented, allowing the module to spontaneously assign and learn diverse loads to several parts of the input system. Xu et al. [13] examine the AI application to enhance risk management in financial services. A comprehensive study exposes that AI methods, mainly DL and ML methods mainly improve the efficiency and accuracy of assessing risk and process management.

In [14], this research uses higher frequency trading volume data in the financial area for applying the LSTM method for risk management purpose. By integrating higher frequency data comprising information on trading volume with the LSTM technique, we develop an LSTM-RV dynamic estimation method for gathered instability. Utilizing a semi parametric Extreme Value Theory (EVT) method, we predict the percentage of return for constructing effective risk management techniques. Murugan [15] concentrated on investigating catastrophes to develop a timely warning structure for handling financial risk. Financial academics and experts are increasingly attentive for developing big-data financial risk control and prevention abilities depending on innovative technology such as ML, NN, big data, and quickening the execution of intellectual prevention of risk and manage platforms.

Nimmala [16] examines the meeting of climate risk and ML models in the financial market, concentrating on using ML procedures for improving the authentication of climate risk methods. Because of the rising importance of accurately controlling and evaluating climate-related risk in the financial sectors, conventional techniques exhibit their insufficiencies in challenging the unpredictability and complexities of climate change. By directing a wide study of top-down and bottom-up techniques, this study highlights utilizing ML procedures to boost the consistency of financial risk assessments, enhance predictive accuracy and control non-linearity. Huang et al. [17] focus on the AI application in the credit risk and market risk of financial derivatives and explore the ability of ensemble learning procedures and DL methods to predict risk. By proposing methods like temporal convolutional network (TCN), LSTM, gradient boosting tree (XGBoost), logistic regression, and support vector machine (SVM) the performance and applicability of various methods in financial data demonstrating are examined. This paper displays that DL methodologies may manage ensemble-learning algorithms, and time-series characteristics have higher estimation stability and accuracy in identifying credit risk.

3. Proposed Methodology

In this study, we have presented an IRMFC-PNFGMOA model. The main intention of IRMFC-PNFGMOA technique is to analyse and develop effective methodologies for measuring and managing financial risk in dynamic market conditions. It includes 4 main steps such as Z-score normalization using data pre-processing, AOA-based feature selection, PNFG based on the process of classification, and GO-based parameter tuning. Fig. 1 depicts the complete working process of IRMFC-PNFGMOA method.

3.1. Pre-processing: Z-score normalization

At first, the data pre-processing stage applies Z-score normalization to clean, transform, and structure raw data to improve the quality [18]. This method also called standardization is a statistic model applied for scaling financial risk data by converting it into the normal standard distribution with a standard deviation of 1 and a mean of 0. It assistances in financial risk management by removing biases supported by dissimilar scales of financial signs, permitting for more correct evaluations and risk calculations. Transforming raw risk metrics into normalized values, it improves the performance of ML methods in financial risk prediction. It is mainly beneficial to detect anomalies, as great values in financial data might specify possible anomalies or risks. This model guarantees that risk features with dissimilar units and sizes do not disproportionately influence risk assessment methods. Finally, it enhances the consistency of financial crisis detection and selection risk study.

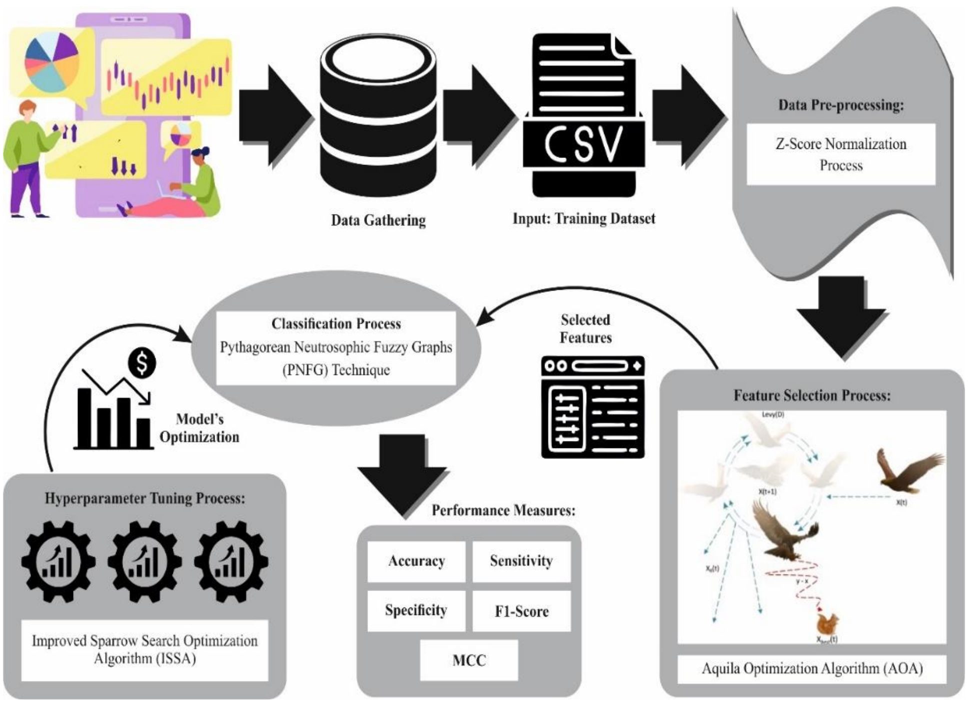

Figure 1. Complete Working Process of IRMFC-PNFGMOA method

3.2. Feature Selection: AOA

Next, the AOA has been deployed for the selection of feature process to identify and retain the most relevant features from input data [19]. The hunting approaches of Aquila birds that incorporate exploratory and exploitative behaviour for discovering the optimal solutions, act as the algorithm for AOA. To establish which feature subset is most significant, this model mimics these behaviours in the process of feature selection (FS). A population of promising solutions (feature sub-sets) is initialized by the model, and every solution is measured based on a fitness function (FF) that estimates its quality level. Now, the FF evaluates the model precision depending on the features that have been selected, penalizing over-FS to prevent overfitting. Fig. 2 represents the flowchart of AOA.

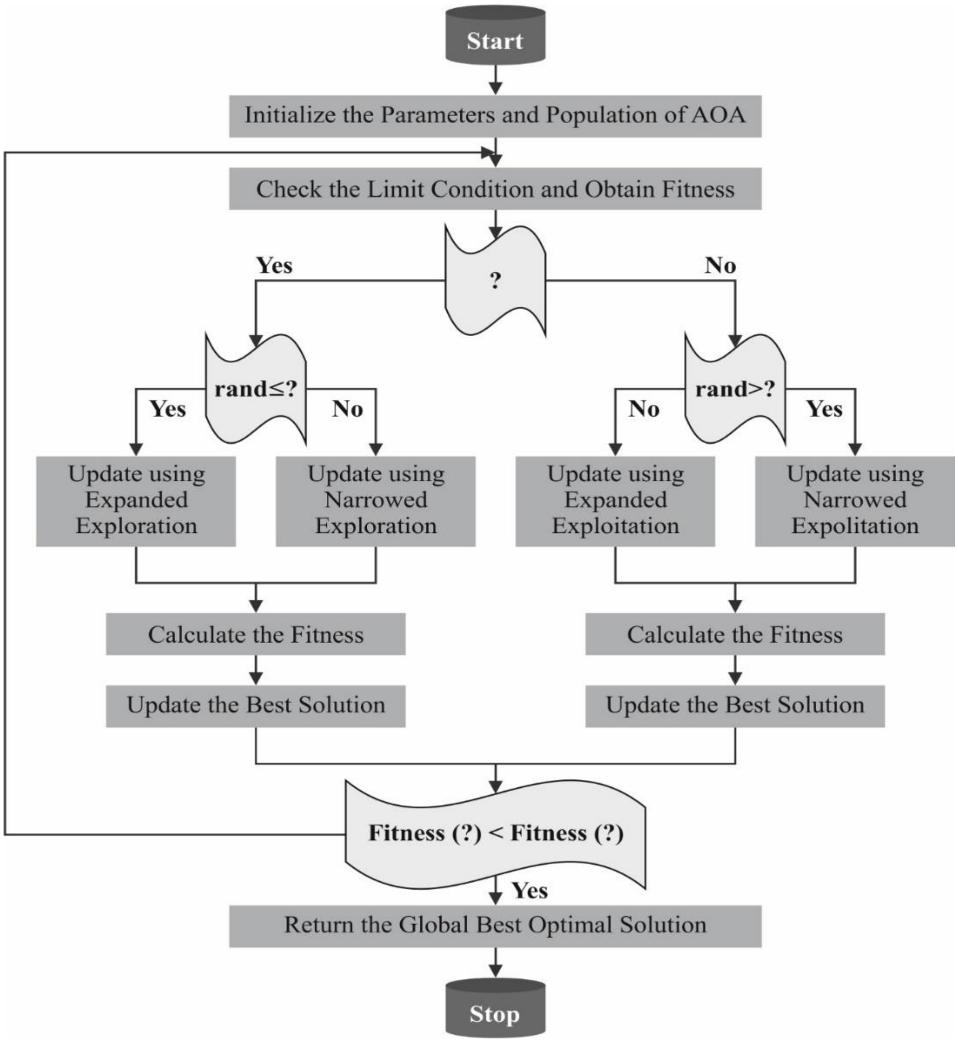

Figure 2. Flowchart of AOA

The FF $J()$ is provided by:

$$J(F) = Accuracy(F) - \lambda \cdot |F| \qquad (1)$$

Whereas λ represents regularization term for penalizing larger feature sets, $|F|$ denotes feature counts in the set. There are dual important phases to the optimization procedure:

Exploration stage: By fine-tuning every feature subset's location, the model searches for fresh, viable locations of the feature area. The equation for the location upgrade is given by:

$$F_{new} = F_{old} + r_1 \cdot (X_{mean} - r_2 \cdot F_{old}) \qquad (2)$$

Here, r_1, r_2 are random variables in the range [0,1], X_{mean} is the average position of the population. F_{old} and F_{new} represent the old and new feature positions.

Exploitation stage: The model then focuses on local developments to hone in on the most possible ideas after they have been recognized. The highest solutions observed thus far are used by changing the location-updated equation.

The model iterates amongst these phases until a stop condition (like the maximal iteration counts or convergence) is suited.

The best features subset for established by this Algorithm 1, which examines the feature space and dynamically adjusts amongst the exploitation and exploration stages. Efficiency of the model is guaranteed and overfitting is prevented by striking a balance between the feature set size and classification precision.

Algorithm 1: Pseudocode of AOA

```
Input: population size, Feature set F, max  iterations
Output: Best feature sub-set
Start AOA
    Initialization population of features
        While iteration < max_iterations do
        For every feature set F in population do
            Compute fitness J(F)
        If exploration stage then
            Update location utilizing exploration equation
        Else
            Update location utilizing exploitation equation
        End if
         End For
         If stopping conditions met then
            Stop
        End if
        End While
        Return Best feature subset
End AOA
```

The fitness function (FF) deliberates the classification precision and the designated feature amounts. It maximizes the classification accuracy and decreases the set size of the chosen characteristics. Hence, the succeeding FF is applied for evaluating individual solutions, as existing in Eq. (3).

$$Fitness = \alpha * \ ErrorRate + (1 - \alpha) * \frac{\#SF}{\#All\_F} \tag{3}$$

Here, $ErrorRate$ meaning that classification error rate employing the chosen attributes. $ErrorRate$ is measured as the incorrect percentage categorized to the sums of classifications completed, stated as a value among (0,1). $\#SF$ refers to chosen feature counts and $\#All\_F$ is the whole feature amounts in the novel data set. α was utilized for controlling the significance of classification quality and. subset length In this tests, α is fixed to 0.9.

3.3. Classification Method: PNFG

For the process of classification, the proposed IRMFC-PNFGMOA model designs the PNFG technique [20]. An intuitionistic fuzzy set 1 on universe Y is specified by $I = \{< s, \mu_I(s), \sigma_I(s) >: s \in Y\}$ here μ_I, σ_I from Y to [0,1] so that $0 \leq \mu_I(s) + \sigma_I(s) \leq 1$ for any one of $s \in Y$. $\sigma_I(s)$ and $\mu_I(s)$ are the non- and membership grade of s respectively.

A neutrosophic set N in Y is expressed by $N = \{(\text{ŧ}, \mu_N(\text{ŧ}), \eta_N(\text{ŧ}), \gamma_N(\$)) | \text{ŧ} \in Y)\}$ now $\mu_N(\text{ŧ})$, $\eta_N(\text{ŧ})$, $\gamma_N(\text{ŧ}) \in [0,1]$ represent indeterminacy, false and truth membership of ŧ of N and $\mu_N(\text{ŧ})$, $\eta_N(\text{ŧ})$, $\gamma_N(\text{ŧ})$ followed by the condition that $0 \leq \mu_N(\text{ŧ}) + \eta_N(\text{ŧ}) + \gamma_N(\text{ŧ}) \leq 3$.

A neutrosophic fuzzy graph is $G=(V,E)$ here $V=\{v_1,v_2,\dots v_n\}$ so that μ_1,β_1 and σ_1 from V to [0,1] specifies level of truth-, indeterminacy- and falsity-memberships of c_i in V respectively, and $0\le\mu_1(c_i)+\beta_1(c_i)+\sigma_1(c_i)\le 3\forall c_i\in V(i=1,\dots,n)$, $E\subseteq V\times V$ with μ_2, β_2 and σ_2 from VxV to [0,1] so that

$$\mu_2(c_ic_j)\le\mu_1(c_i)\wedge\mu_1(c_j)$$

$$\beta_2(c_ic_j)\le\beta_1(c_i)\wedge\beta_1(c_j)$$

$$\sigma_2(c_ic_j)\le\sigma_1(c_i)v\sigma_1(c_j)$$

$0\le\mu_2(c_ic_j)+\beta_2(c_ic_j)+\sigma_2(c_ic_j)\le 3$ for each $(c_ic_j)\in E(i,j=1,2,\dots n)$.

Pythagorean fuzzy set (PFS) P of Y is $P=\{<\mathfrak{r},\mu_P(\mathfrak{r}),\sigma_P(\mathfrak{r})>:\mathfrak{r}\in Y\}$ here $\mu_P(\mathfrak{r})$ and $\sigma_P(\mathfrak{r})$ from Y to [0,1] signifies level of non- and membership of $\mathfrak{r}$ in P correspondingly. $\forall\mathfrak{r}\in Y$, the succeeding condition must be satisfied $0\le\mu_P^2(\mathfrak{r})+\sigma_P^2(\mathfrak{r})\le 1$.

A Pythagorean fuzzy graph (PFG) denotes a duo $G=(V,E)$ with μ_1 and σ_1 from V to [0,1] indicating non-membership and membership functions of V and $0\le\mu_1^2(v)+\sigma_1^2(v)\le 1$ for $v\in V$ so that

$\mu_2(uv)\le\mu_1(u)\wedge\mu_1(v)$,

$\sigma_2(uv)\le\sigma_1(u)v\sigma_1(v)$.

Now μ_2, σ_2 from VxV to [0,1] is the non-membership and membership functions of E, with $0\le\mu_2^2(uv)+\sigma_2^2(uv)\le 1$ for every $uv\in E$.

A Pythagorean Neutrosophic set with falsity, truth as dependent neutrosophic elements [PNS] on non-empty universe Y is $D=\{(d,\mu_D(d),\beta_D(d),\sigma_D(d)):d\in Y\}$, here $\mu_D(d)$, $\beta_D(d)$, $\sigma_D(d)\in[O,1]$, $0\le(\mu_D(d))^2+(\beta_D(d))^2+(\sigma_D(d))^2\le 2$, $\forall d\in Y$. $\mu_D(d)$, $\beta_D(d)$, $\sigma_D(d)$ are the level of indeterminacy, non-membership and membership correspondingly. Now $\beta_D(d)$ is independent, $\mu_D(d)$ and $\sigma_D(d)$ are dependent.

Definition3.1: Pythagorean Neutrosophic Fuzzy Graph (PNFG) is $=(V,E)$, Here $V=\{v_1,v_2,\dots v_n\}$ so that μ_1, β_1 and σ_1 from V to [0,1] with $0\le\mu_1(v_i)^2+\beta_1(v_i)^2+\sigma_1(v_i)^2\le 2\forall v_i$ in V denoted non- , membership and indeterminacy functions respectively and $\subseteq V\times V$ Now, μ_2, β_2 and σ_2 so that

$$\mu_2(v_iv_j)\le\mu_1(v_i)\wedge\mu_1(v_j)$$

$$\beta_2(v_iv_j)\le\beta_1(v_i)\wedge\beta_1(v_j)$$

$$\sigma_2(v_iv_j)\le\sigma_1(v_i)v\sigma_1(v_j)$$

In $0\le((\mu_2(v_iv_j))^2+(\beta_2(v_iv_j))^2+(\sigma_2(v_iv_j))^2\le 2\forall(v_iv_j)\in E$.

Definition3.2: A PNFG $G=(V,E)$ is called complete PNFG (CPNFG) if $\mu_2(v_iv_j)=\mu_1(v_i)\wedge\mu_1(v_j)$, $\beta_2(v_iv_j)=\beta_1(v_i)\wedge\beta_1(v_j)$, $\sigma_2(v_iv_j)=\sigma_1(v_i)v\sigma_1(v_j)$ for every v_i, $v_j\in V$.

Definition3.3: A PNFG $G=(V,E)$ is termed as strong PNFG if

$$\mu_2(v_iv_j)=\min\left(\mu_1(v_i),\mu_1(v_j)\right)$$

$$\beta_2(v_iv_j)=\min\left(\beta_1(v_i),\beta_1(v_j)\right)$$

$$\sigma_2(v_iv_j)=\max(\sigma_1(v_i),\sigma_1(v_j))\forall(v_iv_j)\in E.$$

Definition3.4: Assume that $G=(V,E)$ with μ, β, σ are the non-membership (NMD), indeterminacy (ID) and membership (MD) degree be a PNFG. Afterwards a PNFG $H=(V',E')$ with $V'\subseteq V$ and $E'\subseteq E$, μ', β' and σ' as the NMD, ID, and MD are known as Pythagorean Neutrosophic fuzzy sub-graph (PNFSG) if $\mu'(\mathfrak{d})\le\mu(\mathfrak{d})$, $\beta'(\mathfrak{d})\le\beta(\mathfrak{d})$, $\sigma'(\mathfrak{d})\ge\sigma(\mathfrak{d})$ for $\mathfrak{d}\in V$.

Definition3.5: Let $G'=(V',E\ G''=(V'',E'')\ be$ PNFG with (μ',β',σ') and (μ'',β'',σ'') as their NMD, MD and ID respectively. Moreover the intersection of G' and G'', $G=(V,E)$ is a PNFG here $V=V'\cap V''$ $E=E'\cap E''$ and the NMD, MD and ID of V and E of for every $a,b,r\in V$ so that

(i) $$\mu_1(r)=\begin{cases}\mu_1'(r) & if\ r\ is\ in\ V'\ and\ not\ \text{in}\ V''\\ \mu_1''(r) & if\ r\ is\ in\ V''and\ not\ \text{in}\ V'\\ \mu_1'(r)\wedge\mu_1''(r) & if\ r\ is\ in\ both\ V'\ and\ V''\end{cases}$$

$$\beta_1(r) = \begin{cases} \beta_1'(r) & if\ r\ is\ in\ V'\ and\ not\ \text{in}\ V'' \\ \beta_1''(r) & if\ r\ is\ in\ V''and\ not\ in\ V' \\ \beta_1'(r) \wedge \beta_1''(r) & if\ r\ is\ in\ both\ V'\ and\ V'' \end{cases}$$

$$\sigma_1(r) = \begin{cases} \sigma_1'(r) & if\ r\ is\ in\ V'\ and\ not\ in\ V'' \\ \sigma_1''(r) & if\ r\ is\ in\ V''and\ not\ \text{in}\ V' \\ \sigma_1'(r) V \sigma_1''(r) & if\ r\ is\ in\ both\ V'\ and\ V'' \end{cases}$$

(ii) $$\mu_2\ (ab) = \begin{cases} \mu_2'(ab) & if\ ab\ is\ in\ E'\ and\ not\ in\ E'' \\ \mu_2''(ab) & if\ ab\ is\ in\ E''\ and\ not\ in\ E' \\ \mu_2'(ab) \wedge \mu_2''\ (ab) & if\ ab\ is\ in\ both\ E'\ and\ E'' \end{cases}$$

$$\beta_2(ab) = \begin{cases} \beta_2'(ab) & if\ ab\ is\ in\ E'\ and\ not\ in\ E'' \\ \beta_2''\ (ab) & if\ ab\ is\ in\ E''\ and\ not\ in\ E' \\ \beta_2'(ab) \wedge \beta_2''(ab) & if\ ab\ is\ in\ both\ E'\ and\ E'' \end{cases}$$

$$\sigma_2\ (ab) = \begin{cases} \sigma_2'\ (ab) & if\ ab\ is\ in\ E'\ and\ not\ in\ E'' \\ \sigma_2''(ab) & if\ ab\ is\ in\ E''and\ not\ in\ E' \\ \sigma_2'(ab) \vee \sigma_2''(ab) & if\ ab\ is\ in\ both\ E'and\ E'' \end{cases}$$

Definition3.6: Consider $G' = (V', E)$, $G'' = (V'', E'')$ is PNFG with (μ_1', β_1', σ_1'), (μ_1'', β_1'', σ_1'') and (μ_2', β_2', σ_2'), (μ_2'', β_2'', σ_2''), are the NMD, MD and ID of the edges and vertices respectively. Moreover the union of G' & G'', $G = (V, E)$ specifies a PNFG here $V = V' \cup V''$ $E = E'UE''$ and the NMD, MD and ID of edges (E), and vertices (V) of G for every $g, h \in V$ so that

(i) $$\mu_1(g) = \begin{cases} \mu_1'(g) & if\ g\ is\ in\ V'\ and\ not\ in\ V'' \\ \mu_1''(g) & if\ g\ is\ in\ V''and\ not\ in\ V' \\ \mu_1'(g) \vee \mu_1''(g) & if\ g\ is\ in\ V'\ or\ V'' \end{cases}$$

$$\beta_1(g) = \begin{cases} \beta_1'(g) & if\ g\ is\ in\ V'\ and\ not\ in\ V'' \\ \beta_1''(g) & if\ g\ is\ in\ V''and\ not\ in\ V' \\ \beta_1'(g) v \beta_1''(g) & if\ g\ is\ in\ V'\ or\ V'' \end{cases}$$

$$\sigma_1(g) = \begin{cases} \sigma_1'(g) & if\ g\ is\ in\ V'\ and\ not\ in\ V'' \\ \sigma_1''(g) & if\ g\ is\ in\ V''\ and\ not\ in\ V' \\ \sigma_1'(g) \wedge \sigma_1''(g) & if\ g\ is\ in\ V'\ or\ V'' \end{cases}$$

(ii) $$\mu_2(gh) = \begin{cases} \mu_2'(gh) & if\ gh\ is\ in\ E'\ and\ not\ in\ E'' \\ \mu_2''(gh) & if\ gh\ is\ in\ E''\ and\ not\ in\ E' \\ \mu_2'(gh) v \mu_2''(gh) & if\ gh\ is\ in\ E'\ or\ E'' \end{cases}$$

$$\beta_2(gh) = \begin{cases} \beta_2'(gh) & if\ gh\ is\ in\ E'\ and\ not\ in\ E'' \\ \beta_2''(gh) & if\ gh\ is\ in\ E''\ and\ not\ in\ E' \\ \beta_2'(gh) v \beta_2''(gh) & if\ gh\ is\ in\ E'\ or\ E'' \end{cases}$$

$$\sigma_2(gh) = \begin{cases} \sigma_2'(gh) & if\ gh\ is\ in\ E'\ and\ not\ in\ E'' \\ \sigma_2''(gh) & if\ gh\ is\ in\ E''\ and\ not\ in\ E' \\ \sigma_2'(gh) \wedge \sigma_2''(gh) & if\ gh\ is\ in\ E'\ or\ E'' \end{cases}$$

Note: If $G = (V, E, \rho, \gamma)$ where $\rho = (\mu_1, \beta_1, \sigma_1)$ and $\gamma = (\mu_2, \beta_2, \sigma_2)$ denotes the MD, ID and NMD of the vertices and edges of PNFG respectively, the above-mentioned notions are utilized.

Definition3.7: A Pythagorean Neutrosophic path $P(PNP)$ in PNG $G = (V, E, \rho, \gamma)$ specifying an arrangement of diverse vertices $v_0, v_1, \dots v_n$ (leaving v_0, v_1) so that $\gamma(v_{i-1}, v_i) > 0$, $i = 1$ to n, here n indicates length of PNP. The consecutive pair of the PNP are known as edges.

3.4. Parameter Tuning: GO

In addition optimize model performance; the GO algorithm is utilized for hyperparameter tuning to ensure that the best hyperparameter is selected for enhanced accuracy [21]. Its major design stimulation derives from the reflection mechanisms and learning of individuals in their developing process in society Learning is the individual growing process by attaining experience from the external world. Refection is the method of checking the individual's deficiency and fine-tuning the individual is learning approaches to assist the development of individual. The learning process as opposing the differences between individuals, exploring the reason for these gaps and learning from them. The mathematical expression is given:

$$\overrightarrow{x_\iota}^{It+1} = x\vec{\iota}^{It} + K\vec{A}_1 + K\vec{A}_2 + K\vec{A}_2 + K\vec{A}_3 + K\vec{A}_4 \quad (4)$$

Here $K\vec{A}_k, (k = 1,2,3,4)$ specifies the knowledge attained by the ith individual from the kth group of gap. Refection level is an individual must check and compose for deficiency in each feature and experience should be maintained. Once the lesson of a certain feature cannot be rectified, the preceding knowledge is abandoned, and systematically learning is implemented again. The reflective method of GO is given.

$$x_{ij}^{It+1} = \begin{cases} \begin{cases} lb + r_4 \times (ub - lb) if r_3 < AF \\ x_{ij}^{It} + r_5 \times \left(R_j - x_{ij}^{It}\right) \ else \end{cases} & if\ r_2 - P_3 \\ x_{i,j}^{It}\ else \end{cases} \quad (5)$$

$$AF = 0.01 + 0.99 \times \left(1 - \frac{FES}{\text{Max}FEs}\right) \quad (6)$$

Now lb and ub represents the lower and upper bounds of searching area, and r_2, r_3, r_4, r_5 are uniformly distributed arbitrary numbers in the range $[0,1]$. The value of P_3 controls the likelihood of refection and is set to 0.3. R_j indicates an individual at the higher level and it functions as a reflective learning guide for existing individual i. The attenuation factor (AF) is formed by the existing number of evaluations (FES) and the maximum number of evaluations (MaxFEs).

The GO method originates a FF to reach great performance of classification. It establishes a progressive number to characterize the enriched outcome of the candidate solutions. In this paper, the minimization of the classification rate of error is verified as the GG, as provided in Eq. (7).

$$fitness(x_i) = ClassifierErrorRate(x_i)$$
$$= \frac{no\ of\ misclassified\ samples}{Total\ no\ of\ samples} * 100 \quad (7)$$

4. Performance Validation of Financial Risk Detection

The performance evaluation of the IRMFC-PNFGMOA approach is studied under German credit dataset [22]. This dataset holds 1000 instances under dual class labels such as financial crisis with 300 samples and non-financial crisis with 700 samples. The complete information on this dataset. The total no. of features are 24 but only 18 features were selected.

The financial risk detection result of IRMFC-PNFGMOA algorithm is determined under different epochs in Table 1. The table values state that the IRMFC-PNFGMOA methodology has properly identified all the samples. On 500 epochs, the IRMFC-PNFGMOA technique provides an average $accu_y$ of 89.81%, $sens_y$ of 89.81%, $spec_y$ of 89.81%, $F1_{score}$ of 91.53%, and MCC of 83.60%. Besides, based on 1000 epochs, the IRMFC-PNFGMOA technique provides an average $accu_y$ of 90.95%, $sens_y$ of 90.95%, $spec_y$ of 90.95%, $F1_{score}$ of 92.98%, and MCC of 86.68%. Moreover, on 1500 epochs, the IRMFC-PNFGMOA approach offers an average $accu_y$ of 93.90%, $sens_y$ of 93.90%, $spec_y$ of 93.90%, $F1_{score}$ of 95.10%, and MCC of 90.43%. In addition, on 2000 epochs, the IRMFC-PNFGMOA system delivers an average $accu_y$ of 94.88%, $sens_y$ of 94.88%, $spec_y$ of 94.88%, $F1_{score}$ of 95.97%, and MCC of 92.12%. In addition, depending upon 2500 epochs, the IRMFC-PNFGMOA algorithm offers an average $accu_y$ of 95.14%, $sens_y$ of 95.14%, $spec_y$ of 95.14%, $F1_{score}$ of 96.11%, and MCC of 92.35%. At last, for 3000 epochs, the IRMFC-PNFGMOA system provides an average $accu_y$ of 95.81%, $sens_y$ of 95.81%, $spec_y$ of 95.81%, $F1_{score}$ of 96.61%, and MCC of 93.31%.

Table 1: Financial risk detection of IRMFC-PNFGMOA model under distinct epochs

Class Labels	$Accu_y$	$Sens_y$	$Spec_y$	$F1_{Score}$	**MCC**
Epoch - 500					
Financial Crisis	81.33	81.33	98.29	87.77	83.60
Non-Financial Crisis	98.29	98.29	81.33	95.29	83.60
Average	**89.81**	**89.81**	**89.81**	**91.53**	**83.60**
Epoch - 1000					
Financial Crisis	82.33	82.33	99.57	89.82	86.68
Non-Financial Crisis	99.57	99.57	82.33	96.14	86.68

Average	**90.95**	**90.95**	**90.95**	**92.98**	**86.68**
Epoch - 1500					
Financial Crisis	88.67	88.67	99.14	93.01	90.43
Non-Financial Crisis	99.14	99.14	88.67	97.20	90.43
Average	**93.90**	**93.90**	**93.90**	**95.10**	**90.43**
Epoch - 2000					
Financial Crisis	90.33	90.33	99.43	94.26	92.12
Non-Financial Crisis	99.43	99.43	90.33	97.68	92.12
Average	**94.88**	**94.88**	**94.88**	**95.97**	**92.12**
Epoch - 2500					
Financial Crisis	91.00	91.00	99.29	94.46	92.35
Non-Financial Crisis	99.29	99.29	91.00	97.75	92.35
Average	**95.14**	**95.14**	**95.14**	**96.11**	**92.35**
Epoch - 3000					
Financial Crisis	92.33	92.33	99.29	95.19	93.31
Non-Financial Crisis	99.29	99.29	92.33	98.03	93.31
Average	**95.81**	**95.81**	**95.81**	**96.61**	**93.31**

The comparative outcomes of IRMFC-PNFGMOA method with existing methodologies are illustrated in Table 2 [23-24]. The simulation outcome stated that the IRMFC-PNFGMOA approach outperformed better performances. Based on $Sens_y$, the IRMFC-PNFGMOA approach has higher $Sens_y$ of 95.81% while the ODL-FCP, QABOLSTM, LSTM-RNN, Olex-GA, Genetic ant colony, Ant colony, and AdaBoost approaches have lesser $Sens_y$ of 89.07%, 86.04%, 80.71%, 81.48%, 87.43%, 93.12%, and 70.57%, respectively. Besides, depend upon $Spec_y$, the IRMFC-PNFGMOA technique has better $Spec_y$ of 95.81% where the ODL-FCP, QABOLSTM, LSTM-RNN, Olex-GA, Genetic ant colony, Ant colony, and AdaBoost methodologies have minimal $Spec_y$ of 95.01%, 92.78%, 87.55%, 86.20%, 94.31%, 94.48%, and 62.88%, correspondingly. Moreover, with respect $Accu_y$, the IRMFC-PNFGMOA system has greater $Accu_y$ of 95.81% whereas the ODL-FCP, QABOLSTM, LSTM-RNN, Olex-GA, Genetic ant colony, Ant colony, and AdaBoost algorithms have minimal $Accu_y$ of 93.40%, 90.91%, 84.79%, 83.47%, 90.85%, 93.23%, and 66.69%, respectively. At last, based on $F1_{Score}$, the IRMFC-PNFGMOA system has maximum $F1_{Score}$ of 96.61% while the ODL-FCP, QABOLSTM, LSTM-RNN, Olex-GA, Genetic ant colony, Ant colony, and AdaBoost techniques have inferior $F1_{Score}$ of 91.68%, 89.21%, 87.05%, 85.08%, 91.29%, 93.76%, and 69.54%, correspondingly.

Table 2: Comparative analysis of IRMFC-PNFGMOA mode with existing models

Technique	$Sens_y$	$Spec_y$	$Accu_y$	$F1_{Score}$
IRMFC-PNFGMOA	95.81	95.81	95.81	96.61
ODL-FCP	89.07	95.01	93.40	91.68
QABOLSTM	86.04	92.78	90.91	89.21
LSTM-RNN	80.71	87.55	84.79	87.05
Olex-GA	81.48	86.20	83.47	85.08
Genetic ant colony	87.43	94.31	90.85	91.29
Ant colony Model	93.12	94.48	93.23	93.76
AdaBoost Method	70.57	62.88	66.69	69.54

Table 3 established the computation time (CT) of IRMFC-PNFGMOA algorithm with existing techniques. The results suggest that the proposed IRMFC-PNFGMOA method gets lesser CT outcome of 5.85min. While, the ODL-FCP model, Genetic ant colony method, and AdaBoost technique have obtained somewhat lesser CT of 11.93min, 8.28min, and 11.84min, respectively. Meanwhile, the QABOLSTM system, LSTM-RNN approach, Olex-GA model, and Ant colony method have obtained greater CT of 25.78min, 20.24min, 26.16min, and 26.80min, correspondingly.

Table 3: CT outcome of IRMFC-PNFGMOA model with existing classifiers

Classifiers	**Computational Time (min)**
IRMFC-PNFGMOA	5.85
ODL-FCP	11.93
QABOLSTM	25.78
LSTM-RNN	20.24
Olex-GA	26.16
Genetic ant colony	8.28
Ant colony Model	26.80
AdaBoost Method	11.84

5. Conclusion

In this manuscript, we develop an IRMFC-PNFGMOA. The main intention of IRMFC-PNFGMOA technique is to analyse and develop effective methodologies for measuring and managing financial risk in dynamic market conditions. Initially, the data pre-processing stage applies Z-score normalization to clean, transform, and structure raw data to improve the quality. Besides, the AOA has been deployed for the selection of feature process to identify and retain the most relevant features from input data. For the classification process, the proposed IRMFC-PNFGMOA model designs PNFG technique. To further optimize model performance, the GO algorithm is utilized for hyperparameter tuning to ensure that the best hyperparameter are selected for enhanced accuracy. To exhibit the enhanced performance of the presented IRMFC-PNFGMOA model, a comprehensive experimental analysis is made. The comparative results reported the improvised characteristics of the IRMFC-PNFGMOA model.

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