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Variational Neural Network Optimized with Lyrebird Optimization Algorithm for Analysis and Empirical Evidence of Using Data Mining in Financial Risk Prevention Research

Abstract: - In the contemporary landscape of global finance, the effective prevention and mitigation of financial risks have become pivotal for the stability, resilience, and sustainable growth of financial institutions and markets. As financial instruments and markets continue to evolve in complexity, the need for a thorough analysis of risk prevention strategies has become increasingly apparent. In this manuscript, Variational Neural Network (VNN) optimized with lyrebird optimization algorithm (VNN-LOA) is proposed. Initially data is taken from machinehack-financial risk prediction. Afterward the data is fed to Adaptive Variational Bayesian Filter (VBF) based pre-processing process. The pre-processing output is provided to the Variational Neural Network (VNN) to effectively classify financial risk prevention as either involving risk or no risk. The learnable parameters of the VNN are optimized using lyrebird optimization algorithm (LOA). The proposed method is implemented in MATLAB and the efficiency of the proposed method DM-FRP-VNN-COA is estimated with the help of several performances evaluating metrics like, accuracy, precision, recall, f1-score, sensitivity, specificity, computational time, and ROC are analyzed. The proposed DM-FRP-VNN-LOA method attains 38.88%, 35.75%, and 33.16% higher accuracy for risk classification; 34.31%, 38.47% and 37.23% higher accuracy for no risk classification; 22.63%, 33.27% and 21.49% high precision for risk classification; 22.63%, 33.27% and 21.49% high precision for no risk; 35.136%, 39.04% and 38.81% lower computation Time compared with the existing method like data mining using financial risk prevention based back propagation neural network (DM-FRP-BPNN), data mining using financial risk prevention based machine learning (DM-FRP-ML), and data mining using financial risk prevention based convolutional neural network (DM-FRP-CNN) respectively.

Keywords: Financial Risk Prevention, Adaptive Variational Bayesian Filter, Variational Neural Network, Lyrebird Optimization Algorithm.

I. INTRODUCTION

Financial risk prevention is an essential component of strategic management and making a decision. Within the realm of finance [1]. In the dynamic and complex world of financial markets, organizations face various uncertainties and potential threats that can impact their financial stability and performance [2]. Financial risk refers to the probability of adverse outcomes that may affect the value of financial assets, liabilities, income streams, or the overall financial health of an entity [3]. Financial risk can currently be analyzed in a variety of ways [4]. For various reasons, various researchers have looked into a variety of strategies for managing corporate financial risk [5]. The following techniques are included in the risk analysis approach: analyses of financial statements, financial indexes, and expert opinion techniques [6]. Analysis of financial statements is a process that uses various reporting data from businesses to find, identify, analyze, judge, and decide financial risks in accordance with certain standards [7].

Financial statement analysis's primary goal is to lessen decision uncertainty by turning a substantial quantity of report data into knowledge relevant to a particular decision [8]. Common methods used in analysis of financial statements includes ratio analysis, Factor analysis, comparative analysis, thorough analysis, and assessment [9]. The primary goal of financial risk prevention is to identify, assess, and mitigate the potential risks that an organization may encounter in its financial operations [10]. This proactive approach helps safeguard against unexpected events, market fluctuations, and economic uncertainties that could negatively impact the financial position of a business [11]. Different types of financial risk can appear, including operational risk, credit risk, systemic, market, and liquidity risks [12]. Examples of market risk include fluctuations in stock prices, commodities prices, interest rates, and exchange rates [13].

The potential for monetary loss due to a counterparty's or borrower's default is known as credit risk [14]. An organization runs the risk of liquidity when it is unable to pay its short-term debts [15]. Losses that could be brought about by internal procedures, internal systems, or human error are included in operational risk [16]. Widespread disruptions in the financial system are referred to as systemic risk. In response to these diverse risks, organizations employ a range of strategies and risk management to prevent or minimize the impact of adverse events [17]. This may include hedging strategies, diversification of investments, the use of derivatives, setting risk limits, and implementing robust internal controls and compliance measures [18].

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In order to keep business operations from deviating from the expected operating trajectory, financial risk analysis and early warning is a real-time management control technique and early warning system [19]. In order to forecast the company's risk status, a review of its financial records and associated company operations is necessary to obtain an early financial warning of the company's position. As markets continue to evolve and globalize, the importance of effective financial risk prevention becomes increasingly prominent, making it a critical component of modern financial management practices [20].

The main contributions are summarized as follows,

- Variational Neural Network Optimized with Lyrebird Optimization Algorithm for analysis of using data mining in financial risk prevention (DM-FRP-VNN-LOA) is proposed.
- The data is taken from Machine Hack-financial risk prediction dataset.
- The data is fed to Adaptive Variational Bayesian Filter (AVBF) based pre-processing process.
- From the result it concludes that the proposed DM-FRP-VNN-LOA method is better compared with existing methods like DM-FRP-BPNN, DM-FRP-ML, and DM-FRP-CNN.

The following is the order of the remaining sections of the document. sector 2 discusses relevant work, sector 3 outlines the suggested technique, sector 4 discusses the result and discussion, and sector 5 concludes.

II. METHODOLOGY

Here we reviewed some papers based on Preventing significant financial risk with data mining and machine learning as follows,

Wang and Yu [21] have suggested the development and empirical examination of the data mining algorithm-based model of early warning system for finances the company. The theories of data mining technology and this study introduces early warning systems for financial risk. The research approach used in early financial risk warning model is then covered in detail, along with the 3 data mining approaches that were employed in this study. Ultimately, the theoretical data is combined with the real-world conditions of listed corporations in our nation to create the Early Warning Index System for Financial Risk.

Gao [22] have demonstrated the reduction of financial risk through data mining and machine learning. In order to improve an enterprise's capacity to manage create a comprehensive enterprise financial risk assessment index system, lower labor costs, lower financial losses, and boost investor confidence in business finance listed companies' financial risk analysis uses data mining methods and deep learning technology in an artificial intelligence setting. In light of this, an interactive mining-based analysis technique for financial risk avoidance was introduced. A unique risk analysis model was developed to examine the crucial elements related to the many financial risks that listed companies face.

Qin [23] have presented a study on the convolutional neural network-based financial risk forecast model of listed corporations. As China's market economy continually advances, numerous publicly traded companies were presented with expansive prospects for growth within the market-driven environment. However, they concurrently face diverse potential risks that could jeopardize their stability. Financial risks, in particular, pose a significant threat, potentially leading to the imposition of an "ST" label and, in extreme cases, the risk of delisting. Companies that fail to vigilantly address financial issues in their initial stages and implement timely, effective measures may encounter severe financial crises or even bankruptcy later on. Such oversight proves highly detrimental to the subsequent progress and development of these companies.

Jin et al. [24] have presented an examination of financial risk using data mining techniques. The harsh environment of market competitiveness was making risk management more important for the company on a daily basis. The objective that company management continuously works toward is how to assess financial risks that exist in the process and how to warn about them in a timely manner. Numerous internal and external factors impacted early warning studies and organizational financial risk analysis.

Yue et al. [25] have validated the investigation of effective FRM solutions using information fusion technology and the application of BDM to business FRM. The analysis of company financial risks specifically makes use of big data technology, Information fusion, logistic regression, and SVM techniques. Of these, choosing the right financial risk indicators has a significant influence on the SVM-based FRM model's monitoring results. The FRM model that relies on logistic regression is successful in accurately categorizing financial risks, despite the fact that the information fusion-based FRM model incorporates several information sources via an information fusion method.

Shang et al. [26] have established the various financial metrics derived from IoT big data mining. It was shown that the correlations between all financial indicators were useful in selecting financial risk indicators that were more representative. Next, the parallel mining approach, FCM, and parallel rules were used to create the frequent fuzzy option set. This procedure produced fuzzy association rules with the least amount of fuzzy credibility. Lastly, the technique presented in this study was authorized by utilizing corporate financial risk analysis data from listed companies.

Miao et al. [27] have suggested to automatically categorize the information about concealed dangers and extract the coal mines theme, artificial intelligence (AI) technology is used with the Bi-LSTM model. Subsequently, starting with the possibility of a gas explosion in a coal mine, a predictive model for gas safety conditions was formulated. In the end, an intelligent solution and data mining technologies were used to construct an enhanced management and control information system. This system's wide visual display and sophisticated APP processing allow for thorough information analysis. Successfully implemented at the Luxi coal mine, the system has demonstrated positive outcomes, significantly raising the coal mine's efficiency and capacity for safety management.

III. PROPOSED METHODOLOGY

DM-FRP-VNN-LOA is discussed in this section. This section presents the clear description about the research methodology for analysis of financial risk prevention. Block diagram of VNN-LOA is represented in Figure 1. Thus, the detailed description about VNN-LOA is given below,

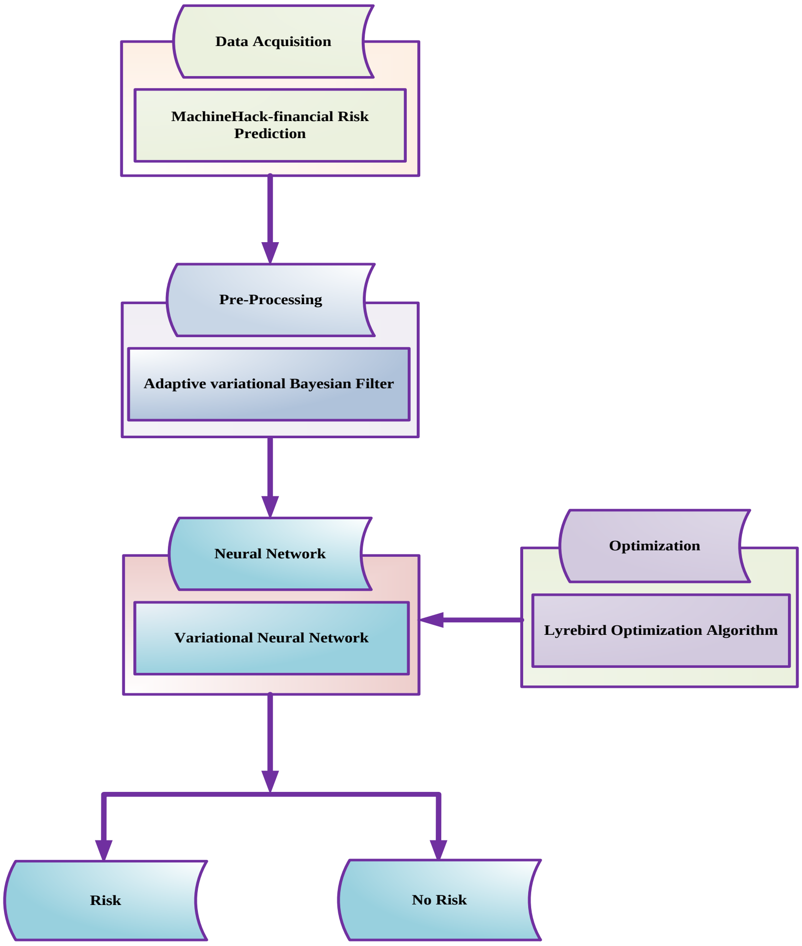

Figure 1: Block diagram of VNN-LOA

A. Data Acquisition

Data is taken from machine hack-financial risk prediction [28]. Any firm cannot overlook even the remotest possibility of financial risk. To ensure that they stay above the crucial threshold, organizations regularly audit their income and expenses. As a data scientist, you have to analyze the provided data in this hackathon to determine whether or not a business is potentially financially vulnerable.

B. Pre-processing by Adaptive Variational Bayesian Filter (AVBF)

This method primarily uses the data’s as input to eliminate any form of noise. It is used to model the noise characteristics and adaptively filter the data. The step for denoising in AVBF [29] is given bellow;

Step 1: In the context of data processing, the state variable (x_t) could represent the true underlying pixel intensities, and the state transition function (f) might model how these intensities evolve over time or space. The observation function (h) relates the true state to the observed data in equation (1) and (2),

$$x_t = f(x_{t-1}, w_t) \tag{1}$$

$$z_t = h(x_t, v_t) \tag{2}$$

Here, w_t is the noise produced by the process (evolution of pixel intensities) and v_t is the observation noise.

Step 2: Using cubature quadrature to approximate integrals. In the context of data processing, this could involve integrating over pixel intensities to compute expectations efficiently.

Step 3: Introduce a variation distribution ($q(x_t)$) to approximate the true posterior distribution of pixel intensities. Optimize the parameters of this distribution to fit the observed data while considering the noise characteristics.

Step 4: Adapt the information filter update to data processing. The observation function (h) might map the true pixel intensities to the observed data. Update the information filter using the cubature rule, considering the noise characteristics of the mammography data's.

Step 5: After the filter update, use the estimated state x_t as the denoised version of the mammography data.

Then, a pre-processed input data is passed to the VNN.

C. Prediction by Variational Neural Network (VNN)

Variational Neural Networks (VNN) [30] represent a class of neural networks. that incorporates variational inference, a technique from probabilistic modeling. VNNs are often used for generative modeling and uncertainty estimation.

In variational inference, the goal is to approximate a complex probability distribution, $p(z|x)$, With a more simpler distribution, $q(z|x)$, parameterized by a set of learnable parameters θ. In the context of VNNs, z typically represents latent variables.

The main equation in variational inference is the ELBO, which is defined as in equation (3),

$$ELBO = Eq_{(z|x;\theta)}[\log p(x,z) - \log q(z|x;\theta)] \tag{3}$$

VNNs incorporate neural networks to parameterize the approximate posterior $q(z|x;\theta)]$ and the likelihood $p(x|z)$. Let $f_{enc(x;\phi)}$ be the neural network encoder and $f_{dec(z;\psi)}$ be the neural network decoder.

Encoder represents the equation (4),

$$q(z|x;\theta)] = N(z; \mu_\theta(x), \sigma_\theta(x)) \tag{4}$$

Here $\mu_\theta(x)$ *and* $\sigma_\theta(x)$ are the encoder's output vectors for mean and standard deviation.

The Decoder represents the equation (5),

$$p(x|z;\psi)] = N(x; \mu_\psi(z), \sigma_\psi(z)) \tag{5}$$

Here $;\mu_\psi(z) and \sigma_\psi(z)$ are the mean and standard deviation vectors output by the decoder.

Objective Function: Maximizing the ELBO is the aim of the VNN training process. This involves minimizing the negative ELBO, which is equivalent to minimizing the following loss function using equation (6),

$$L(\theta,\phi,\psi;x) = -ELBO = -Eq_{(z|x;\theta)}[\log p(x,z) - \log q(z|x;\theta)] \tag{6}$$

Typically, the prior $p(z)$ is considered to resemble a simple distribution, like a unit Gaussian.

Training: The VNN is trained using a related optimization algorithm. The objective function's gradients in relation to the parameters $\theta, \phi, and\, \psi$ are computed through back propagation and used to update the model parameters. Finally, the Variational Neural Network (VNN) is to effectively classify financial risk prevention as either involving risk or no risk. LOA is used in this work to maximize the learnable parameter of the VNN.

D. Proposed Lyrebird Optimization Algorithm

The learnable parameter θ of proposed VNN is optimized using the proposed LOA [31]. This section introduces the Lyrebird Optimization Algorithm (LOA), an innovative bio-inspired metaheuristic algorithm that emulates the actions of wild lyrebirds. Lyrebirds in this situation carefully survey their surroundings before making their move to flee or conceal in hiding. The theory of LOA is explicated and thereafter computationally represented in 2 stages: (i) investigation, utilizing a model of the lyrebird's means of escape, and (ii) utilization, grounded in the simulation of the concealing plan. Among the most well-known native birds of Australia are lyrebirds, which feature distinctive plumes of neutral-colored tail feathers. Figure 2 shows the flowchart of the LOA algorithm. The proposed LOA technique, which is covered below, was created using mathematical modeling of this lyrebird tactic in times of peril.

Step 1: Initialization

The initialization learnable parameter of a θ.

Step 2**:** Random Generation

After starting, the input variables are produced arbitrarily. The condition of explicit hyperparameter determines the optimal selection of fitness values.

Step 3: Fitness Function

Initialization values, result is arbitrary solution. Assessment of fitness values utilizes outcomes of learnable parameter optimization θ. It expressed in eqn (7),

$$Fitness\ function = Optimizing\ (\theta) \tag{7}$$

Step 4: Escaping Strategy (Exploration Phase**)**

By simulating the lyrebird's migration from the area of danger to the areas of safety, this LOA phase involves updating the population member's position in the search space. The lyrebird's capacity to explore new locations in the area of problem-solving and make large positional changes after moving to a safe place is indicative of LOA's global search exploration capability. Every member of the LOA design views the areas inhabited by other population members with higher objective function values as safe zones. Equation (8) can therefore be used to determine the set of safe zones for each member of the LOA.

$$DB_j = \{Z_P, \quad E_P < E_j \ \ and \ \ P \in \{1, 2, ..., M\}\}, \qquad Where\ j = 1, 2, ..., \ M, \tag{8}$$

Here DB_j is the set of places that are safe for jth lyrebirds and Z_P is the Z matrix's th row, which is superior than the jth LOA component in terms of objective function value

It is anticipated In the LOA design, the lyrebird sometimes makes its way to one of these secure locations. Equation (9), which is based on the displacement modeling of lyrebirds carried out in this phase, is utilized to determine a new location for every LOA member. Then, if the value of the goal function is increased, then, in accordance with Equation (10), this new position replaces the appropriate member's previous position.

$$z_{j,i}^{k1} = z_{j,i} + l_{j,i} \cdot \left(SSB_{j,i} - J_{j,i} \cdot z_{j,i}\right) \tag{9}$$

$$Z_j = \begin{cases} Z_j^{k1}, E_j^{k1} \le E_j \\ Z_j \ , \ Else \end{cases} \tag{10}$$

Here, SSB_j is jth Lyrebird's selected safe area $SSB_{j,i}$ is its ith dimension, z_j^{k1} is the new position determined for the jth lyrebird using the proposed LOA's escape strategy, $z_{j,i}^{k1}$ is its ith dimension, E_j^{k1} is its objective function value, $l_{j,i}$ are arbitrary values drawn from the range [0, 1].and $J_{j,i}$ are arbitrary numbers chosen at random to be either 1 or 2.

Step 5: Exploitation Phase for optimizing θ

For the duration of this LOA stage, utilizing the lyrebird's modeling technique, the population member's position is updated in the search space to conceal in its immediate safe region. The lyrebird's position varies somewhat as a result of precisely monitoring the surroundings and taking little steps to get to a good hiding place; this shows how LOA can be used in local search. Equation (11) is used in LOA design to forecast the lyrebird's journey toward the closest acceptable hiding site, hence determining a new location for every LOA member. If, in accordance with Equation (12), this new position enhances the objective function's value, it takes over the connected member's previous role.

$$z_{j,i}^{k2} = z_{j,i} + (1 - 2l_{j,i}) \cdot \frac{vc_i - qc_i}{T} \tag{11}$$

$$Z_j = \begin{cases} Z_j^{k2}, E_j^{k2} \le E_j \\ Z_j \ , \ Else \end{cases} \tag{12}$$

Here, z_j^{k2} is the new location found for the jTH Lyrebird by employing the proposed LOA's hiding technique, $z_{j,i}^{k2}$ is its ith dimension, E_j^{k2} is its value as an objective function, $l_{j,i}$ are the iteration counter and are random values from the range [0, 1].

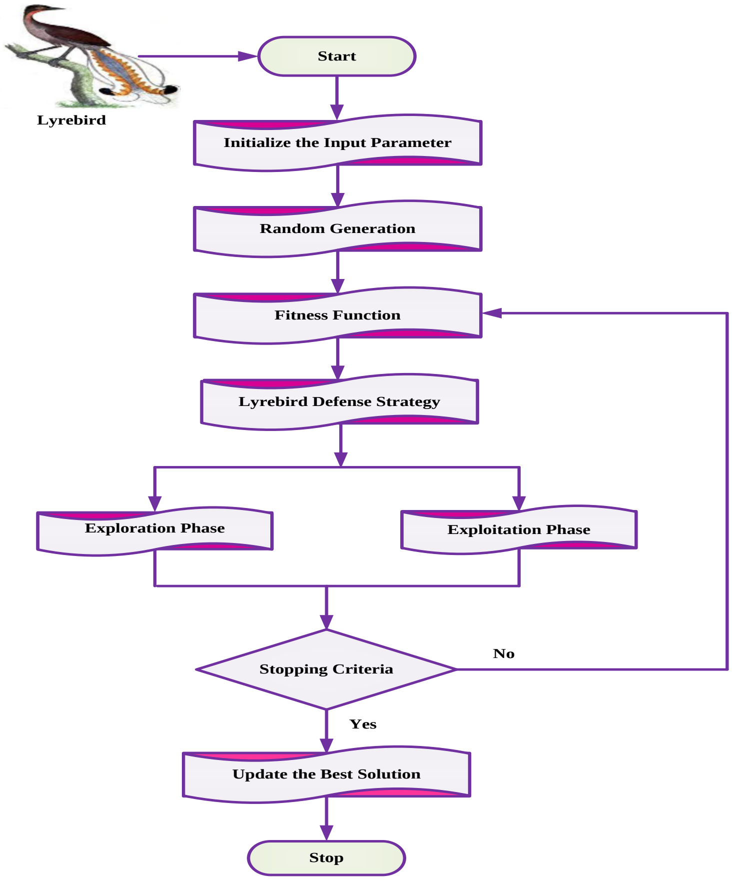

Figure 2: Flowchart of LOA

Step 6: Termination Criteria

Check the requirements for termination. if it is met, the best possible solution has been found; if not, repeat the procedure.

IV. RESULT WITH DISCUSSION

This section covers the experimental results of the proposed method. The proposed approach is then simulated using MATLAB with the performance metrics specified. The proposed DM-FRP-VNN-COA approach is implemented in MATLAB using Machine Hack-financial risk prediction dataset. The obtained outcome of the proposed DM-FRP-VNN-COA approach is analysed with existing systems like DM-FRP-BPNN, DM-FRP-ML, and DM-FRP-CNN respectively.

A. Performance Measures

1) Accuracy

The ratio of the count of accurate predictions to total number of predictions made for a dataset. It is measured through equation (13),

$$Accuracy = \frac{(TP + TN)}{(TP + FP + TN + FN)} \tag{13}$$

Where, TN is represents as true negative, TP is represents true positive, FN is denotes false negative, and FP is indicates false positive.

2) Precision (P)

The measure of precision is which quantifies the count of correct positive prediction made. Equation (14) is used to scale this.

$$\Pr ecision = \frac{TP}{(TP + FP)} \tag{14}$$

3) ROC

An integrated measurement of a measurably effect or phenomena is the ROC. It is scaled by eqn (15),

$$ROC = 0.5 \times \frac{TN}{FP + TN} + \frac{TP}{FN + TP} \tag{15}$$

4) Sensitivity

Sensitivity is described as the proportion of accurately detected samples to the full positive sample. It is calculated by following eqn (16)

$$Sensitivity = \frac{TP}{TP + FN} \tag{16}$$

5) Specificity

The percentage of true negatives that the method correctly identifies is called specificity. It is determined by equation (17),

$$Specificity = \frac{TN}{TN + FP} \tag{17}$$

6) Error Rate

A method's degree of prediction error based on a genuine method is measured by its error rate. Equation (18) scales it.

$$Error\ \ Rate = 100 - Accuracy \tag{18}$$

B. Performance Analysis

Figure 3 to 9 depicts the simulation results of proposed DM-FRP-VNN-LOA method. Then, the proposed DM-FRP-VNN-LOA approach is contrasted with existing techniques like, DM-FRP-BPNN, DM-FRP-ML, and DM-FRP-CNN respectively.

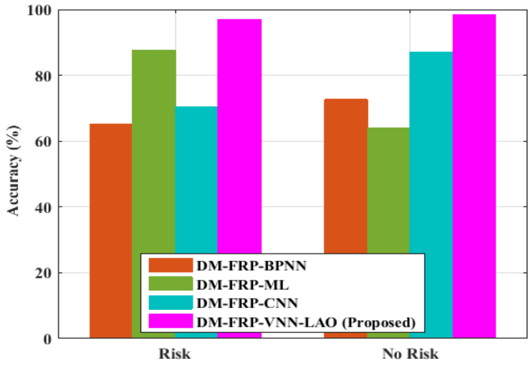

Figure 3: Performance analysis of Accuracy

Figure 3 shows the performance analysis of accuracy. Here, the proposed DM-FRP-VNN-LOA approach achieves more accuracy in risk classification of 38.88%, 35.75%, and 33.16%; and in no risk classification of 34.31%, 38.47%, and 37.23% when compared to existing approaches like DM-FRP-BPNN, DM-FRP-ML and DM-FRP-CNN respectively.

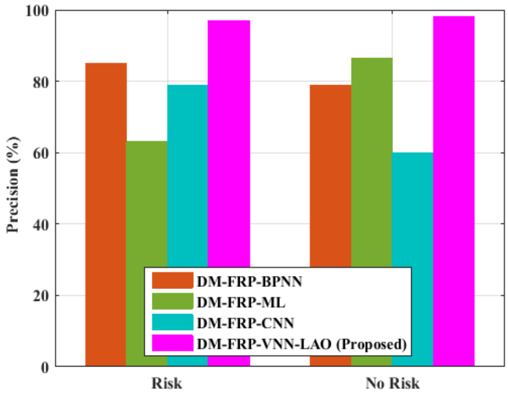

Figure 4: Performance analysis of Precision

Figure 4 shows the performance analysis of precision. The proposed method DM-FRP-VNN-LOA method attains 22.63%, 33.27% and 21.49% high precision for risk classification; 22.63%, 33.27% and 21.49% high precision for no risk classification compared with existing methods like DM-FRP-BPNN, DM-FRP-ML and DM-FRP-CNN respectively.

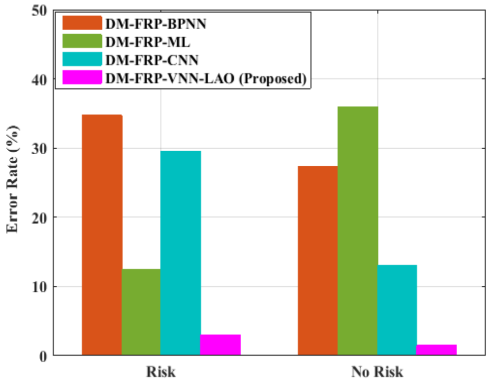

Figure 5: Performance analysis of Error Rate

Figure 5 depicts the analysis of Error Rate. Here, the proposed DM-FRP-VNN-LOA method attains 37.34%, 32.54% and 27.45% lower error rate for risk classification; 39.62%, 34.27% and 35.33% less errors made while classifying no risk as compared to existing methods such as DM-FRP-BPNN, DM-FRP-ML and DM-FRP-CNN correspondingly.

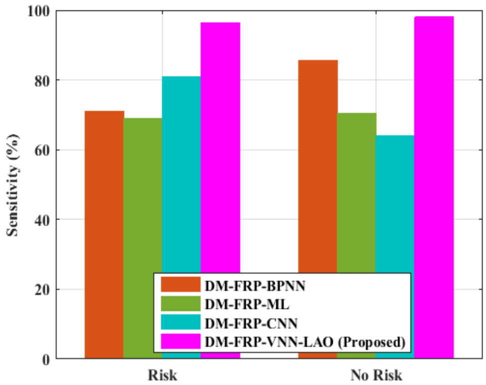

Figure 6: Performance analysis of Sensitivity

Figure 6 depicts the analysis of Sensitivity. Here, the proposed DM-FRP-VNN-LOA method attains 38.71%, 33.44% and 27.05% higher sensitivity for risk classification; 33.36%, 38.05% and 30.41% more sensitivity when classifying no risk in comparison to existing methods such as DM-FRP-BPNN, DM-FRP-ML and DM-FRP-CNN respectively.

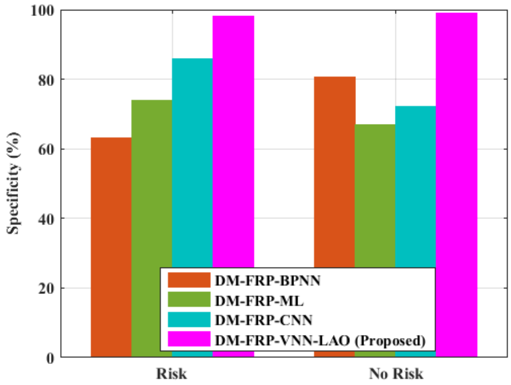

Figure 7: Performance analysis of Specificity

Figure 7 shows the performance analysis of specificity. The proposed method DM-FRP-VNN-LOA attains36.69%, 32.42% and 28.15% high specificity for risk classification; 32.36%, 37.05% and 29.42% more specificity for the no-risk category when compared to existing methods such as DM-FRP-BPNN, DM-FRP-ML and DM-FRP-CNN respectively.

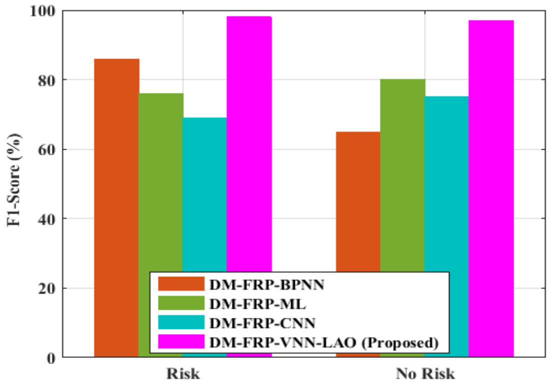

Figure 8: Performance analysis of F1-Score

Figure 8 depicts the analysis of F1-Score. Here, the proposed DM-FRP-VNN-LOA method attains 32.43%, 38.5% and 29.45% higher F1-Score for risk classification; 36.6%, 32.07% and 36.83% greater F1-Score for the no-risk category when compared to existing methods such as DM-FRP-BPNN, DM-FRP-ML and DM-FRP-CNN respectively.

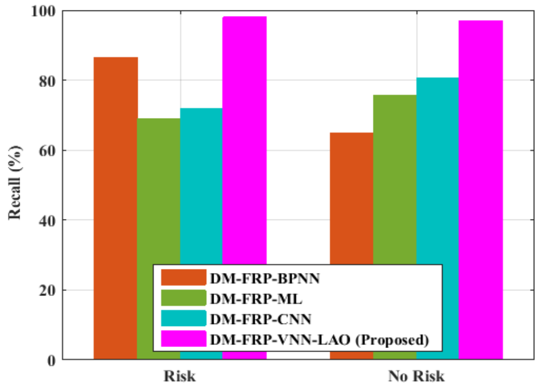

Figure 9: Performance analysis of Recall

Figure 9 shows the performance analysis of recall. The proposed method DM-FRP-VNN-LOA attains 20.76%, 32.67% and 25.89% high recall for risk classification; 21.6%, 30.07% and 28.83% higher recall for no risk classification compared with existing methods such as DM-FRP-BPNN, DM-FRP-ML and DM-FRP-CNN respectively.

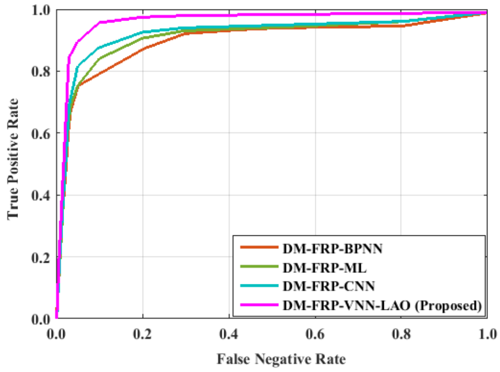

Figure 10: Performance analysis of ROC

Figure 10 depicts the analysis of ROC. Here, the proposed DM-FRP-VNN-LOA method attains 29.29%, 35.35% and 37.95% greater AUC in comparison to existing methods such as DM-FRP-BPNN, DM-FRP-ML and DM-FRP-CNN correspondingly.

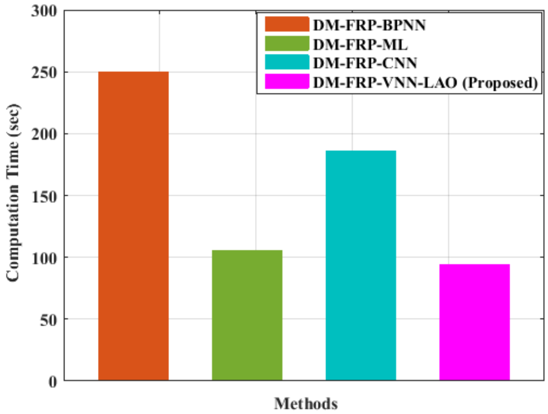

Figure 11: Performance analysis of Computation Time

Figure 11 depicts the performance analysis of Computation Time. This time, the proposed DM-FRP-VNN-LOA approach achieves 35.136%, 39.04%, and 38.81% reduced computing time in comparison to existing approaches like DM-FRP-BPNN, DM-FRP-ML and DM-FRP-CNN respectively.

Discussion

A DM-FRP-VNN-LOA model for analysis of financial risk prevention from machine hack-financial risk prediction dataset is developed in this paper. The DM-FRP-VNN-LOA method involves encompasses AVBF based data pre-processing. Finally, the VNN method is used for effectively classify financial risk prevention as either involving risk or no risk. In the instance of dataset, the average highest outcomes of the approach were compared to the average results given in current methods such as DM-FRP-BPNN, DM-FRP-ML, and DM-FRP-CNN. The proposed DM-FRP-VNN-LOA technique achieves greater accuracy in risk classification of 38.88%, 35.75%, and 33.16%; and higher accuracy in no risk classification of 34.31%, 38.47%, and 37.23%. The proposed method DM-FRP-VNN-LOA method attains 22.63%, 33.27% and 21.49% high precision for risk classification; 22.63%, 33.27% and 21.49% high precision for no risk classification. The proposed DM-FRP-VNN-LOA method attains 37.34%, 32.54% and 27.45% lower error rate for risk classification; 39.62%, 34.27% and 35.33% lower error rate for no risk classification. The proposed method is better for financial risk prevention than previous methods.

V. CONCLUSION

In this manuscript, financial risk prevention analysis based on VNN-LOA is successfully implemented. The proposed DM-FRP-VNN-LOA method is implemented in MATLAB platform using machine hack-financial risk prediction dataset. The proposed DM-FRP-VNN-LOA method attains 37.34%, 32.54% and 27.45% lower error rate for risk classification; 39.62%, 34.27% and 35.33% lower error rate for no risk classifications; 38.71%, 33.44% and 27.05% higher sensitivity for risk classification; 33.36%, 38.05% and 30.41% greater sensitivity for no risk categorization when compared to existing techniques like DM-FRP-BPNN, DM-FRP-ML and DM-FRP-CNN respectively. In conclusion, the integration of a Variational Neural Network (VNN) optimized with the Lyrebird Optimization Algorithm represents a promising approach for advancing research in financial risk prevention through data mining.

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