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Early Warning of Financial Risk Management using AGRNN-COA Approach



Abstract: - Financial risk management was used to protect an entity's financial performance and stability, entails detecting, evaluating, and reducing potential risks, such as credit defaults and market swings. It includes tactics including hedging, diversification, and risk limitation. Financial authorities must immediately responsive for financial risk management system that works with the current economic development. This paper proposes a hybrid approach for early pre-alarm warning of financial risk management system and economic development. The proposed hybrid approach is the combined performance of both the Alternating Graph-Regularized Neural Network (AGRNN) and Crayfish Optimization Algorithm (COA). Commonly it is named as AGRNN-COA technique. The major objective of the proposed approach is to give early pre-alarm warning of financial risk management. AGRNN is designed to give early pre-alarm warning of the financial system of the country. The financial risk management from the AGRNN are optimized by using the COA. By then, the proposed model is implemented in the MATLAB/Simulink working platform and the execution is calculated with the present procedures. The proposed method shows better results in all existing like Financial Risk Management Supervised Algorithm (FRM-SVM), Financial Risk Management Deep Neural Network (FRM-DNN) and Financial Risk Management Heap Based Optimization (FRM-HBO). The accuracy level of proposed FRM-AGRNN-COA approach is 98% that is higher than the other existing methods. The specificity and the F-score of the proposed FRM-AGRNN-COA approach is 99% and 97%. The error rate of the proposed FRM-AGRNN-COA approach is 1.8%, which is very less compared to other existing techniques. From the result, it is conclude that the proposed approach based error is less compared to existing techniques.

Keywords: Credit risk, Risk management, Financial level, Early warning, Economic risk, Weight classifier, Financial management, Alternating Graph-Regularized Neural Network, Crayfish Optimization Algorithm.

I. INTRODUCTION

The progress of the social economy has significantly elevated the importance of the financial market as a vital component of the national economy, representing a key manifestation of a competitive strength of the company [1]. The exponential rise in data accumulation has raised the need for efficient financial information management and structure. Swiftly extracting valuable information and conducting effective analysis and predictions based on this data have become critical focal points in both industrial and academic research [2]. In addition to offering technical support for financial management and investment activities, the investigation of the fundamental characteristics of financial markets and the examination of possible developmental patterns found in data are essential for the steady expansion of financial markets [3, 4]. It is underscored that economic development is intricately linked with financial support, necessitating a robust financial ecosystem [5]. Improved financial ecosystems are essential to ensuring the financial industry continues to grow in a sustainable and healthy manner. Concurrently acting as an effective measure for preventing and resolving financial risks [6].

Despite being crucial for businesses, financial risk management has disadvantages. Especially during catastrophic events, models tend to oversimplify complicated market dynamics by relying on historical data that may not be reliable in predicting future hazards [7]. In difficult financial circumstances, correlation assumptions may break down, resulting in unanticipated losses. Additionally, there is a chance that decision-makers may misinterpret models if they rely too much on them [8]. In illiquid markets, liquidity risk can occur, and measures for risk management might be impacted by legislative changes. Technological malfunctions and other operational hazards increase complexity, and because risks are dynamic, they must always be adjusted [9]. And in the event that the predicted danger never comes to pass, the expense of risk mitigation techniques could be viewed as an opportunity cost. Behavioural elements that affect decision-makers include cognitive biases [10]. Financial risk encompasses a multitude of factors that can impact desired outcomes or yield undesirable effects, thereby influencing the operations of individuals, businesses, investors, and the overall market. On an individual level, financial risk involves the potential loss of investments and the capacity to meet loan obligations. In the realm of business, financial risk can manifest through operational challenges, credit risk (inability to settle debts), and market risk (loss of customers due to competitor innovations, upgrades, and shifts in consumption patterns) [11].

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For governments, financial risk implies challenges in managing inflation, potential defaults on bonds and other debt instruments, and other fiscal uncertainties [12]. Businesses should utilize in order to overcome these constraints.

To overcome the challenges associated with financial risk management, businesses must adopt a nuanced and adaptive approach. While financial models are indispensable, especially during catastrophic events, it's crucial to acknowledge their limitations. Relying solely on historical data may lead to oversimplification of market dynamics, and in times of crisis, correlation assumptions may prove unreliable, resulting in unforeseen losses [13]. Decision-makers should exercise caution not to overly depend on models and be aware of potential misinterpretations. In the face of illiquid markets, regulatory changes, technological malfunctions, and other operational risks, it becomes imperative to continually adjust risk management measures [14]. Recognizing the dynamic nature of risks and incorporating behavioural elements, such as cognitive biases, into decision-making processes is essential. Individuals, businesses, and governments employ a variety of risk management strategies to overcome financial risks [15]. The impact of underperforming assets can be lessened by investors through distributing their holdings across several asset types, including bonds, stocks, and real estate. To lessen their reliance on a single revenue source, companies diversify their clientele, product and service offerings, and geographic marketplaces. To protect against unexpected events, individuals purchase insurance policies covering health issues, property damage, or loss of income [16]. Businesses invest in insurance coverage for various risks, including property, liability, and industry-specific challenges. Regular assessment and monitoring of financial positions are crucial for both individuals and businesses [17]. This involves identifying potential risks and adjusting strategies to adapt to changing economic conditions. In financial markets, individuals use instruments like options or futures contracts to hedge against adverse price movements, while businesses employ hedging strategies, such as futures contracts or derivative instruments, to mitigate risks associated with currency fluctuations, commodity prices, or interest rates [18]. Maintaining emergency funds is essential for individuals to cover living expenses in unforeseen events like job loss or health emergencies. Similarly, businesses establish financial buffers to cover unexpected expenses or periods of reduced cash flow. Strategic planning is fundamental for businesses and governments to develop robust plans considering potential financial risks and including contingency measures. This involves anticipating challenges and having pre-defined responses to navigate uncertainties [19]. Debt management is crucial for individuals to avoid high-interest loans and explore debt consolidation options. Businesses monitor and control debt levels, negotiating favourable terms with creditors to reduce financial strain. Staying informed about relevant regulations and compliance requirements is essential for both businesses and governments. This ensures adherence to laws, avoiding financial penalties and legal risks. Continuous education is key for individuals and businesses to stay informed about economic trends, financial markets, and industry-specific developments. Continuous learning enhances the ability to make informed decisions in a dynamic financial landscape. Scenario analysis is conducted by businesses and governments to evaluate the possible effects on their financial positions of market-related, political, or economic events. This proactive approach helps in preparing for and mitigating the effects of potential risks [20]. By adopting a combination of these strategies and tailoring them to specific circumstances, individuals, businesses, and governments enhance their ability to manage and overcome financial risks, promoting financial stability and resilience. Ultimately, businesses should adopt a holistic strategy that combines quantitative models with qualitative insights and embraces flexibility to effectively navigate the complexities of financial risk management.

Major contribution of this paper as follows;

- Alternating Graph-Regularized Neural Network optimized with Crayfish Optimization Algorithm for early warning of financial risk management (FRM-AGRNN-COA) is proposed.
- Here, the data is collected from the CSMAR dataset.
- The dataset sourced from CSMAR dataset was employed in conducting the pre-processing process using the Tightly-Coupled Iterated Kalman Filter (TCIKF) Technique. This involved a meticulous analysis of the dataset to identify and choose the most relevant data for subsequent analysis.
- In financial risk management, the Alternating Graph-Regularized Neural Network(AGRNN) emerges as a prominent technique. AGRNN's primary function effectively lies in financial risk management.
- To further enhance the early financial risk management, AGRNN utilizes the Crayfish Optimization Algorithm (COA) to fine tune and optimize its financial risk management accuracy.

The document's remaining sectors are organized as follows: Sector 2 discusses recent research work and their background. Sector 3 describes the proposed methodology for early pre-alarm warning of financial risk

management and provides an illustration for the proposed technique AGRNN-COA was used for early warning of financial risk management using hybrid AGRNN-COA method. In sector 4, the discussion and results are explained. Finally, Sector 5 presents the conclusion.

II. METHODOLOGY

Many earlier studies that have been published in literature have relied on the financial risk warning by utilizing a variety of techniques and factors. A small number of them were covered in this article.

Bowen and Lynch [21] have investigated in addition to enhancing infrastructure safety, intelligent sensing, mechanism comprehension, and degradation predictions based on spatiotemporal big data also point to the fundamental ideas and essential technologies that will enable intelligent infrastructure design. The progress of subterranean space usage has resulted in the emergence of three attributes deep, large, and clustered that contribute to the formation of a tri dimensional urban layout. However, the illnesses and deterioration that happen underneath are more subtle and challenging to detect than those that affect structures and bridges above ground. There were still a lot of obstacles to overcome throughout the building and servicing phases. Gao [22] have investigated to enhance businesses' capacity to manage financial risks, lower labour expenses, lower financial losses, boost investors' confidence in business financing, and create an extensive enterprise financial risk assessment index system, an artificial intelligence setting, data mining techniques and deep learning technologies were used for listed businesses' financial risk monitoring. In light of this, an interactive mining-based financial risk avoidance analysis approach is proposed. A unique risk analysis model is created to examine the important elements related to the many financial risks that listed companies face. High-trust norms were discovered through the empirical study of listed firms, and the financial catastrophe of listed corporations was predicted ahead of time. Ouyang and Lai [23] have suggested with a network public opinion index created by text mining as the training set, the suggested Attention-LSTM neural network model was applied to early warning analysis of systemic risk in China. This indicates a non-linear Granger causality exists between systemic risk and network public opinion. The Attention-LSTM neural network performs significantly better than the BP neural network, SVR model, and ARIMA model in terms of early warning effects. This is due to the network's strong generalization ability. The LSTM neural network has increased the systemic risk indicators' average forecast accuracy over short, medium, and long timeframes, demonstrating greater accuracy rates overall. Incorporating the attention mechanism further enhances a neural network model for Attention-LSTM accuracy in all scenarios. Tan et al. [24] have investigated on assessing and predicting financial stability in China by utilizing daily frequency data from various markets. Based on time-varying correlation coefficients, the Dynamic Weighting Method was used to create the ICFS. Using the Markov Regime Switching Model, the ICFS was split into high, medium, and low risk, with a focus on the high-risk regime. Subsequently, the XGBoost model was employed, demonstrating superior performance in early warning of financial risks compared to other machine learning models. In addition, an interpretable framework is presented in the report, which clarifies the real economy, financial institutions, expectations in the market, the real estate sector, and other factors influencing the stability of China's finances. The discovery of eight crucial characteristics and their early warning values, in particular, offers investors, market regulators, and legislators insightful information and a potentially helpful tool to improve resistance to financial hazards.

Guan et al. [25] have suggested the hazards associated with financial management that China's rural family farms face by creating a REW model for family farm financial operations. The model integrates BPNN, RST, and risk assessment principles to construct an effective REW index system. The research elaborates on the concept of BPNN and combines it with RST to establish a comprehensive framework for evaluating and predicting financial risks in family farms. Through the application of the designed REW model, it aims to provide accurate predictions of financial operations, emphasizing the importance of proactively managing both operation and profitability risks. The proposed BPNN-based REW model offers a feasible approach under the investigated RST, contributing to the theoretical foundation for financial operation risk early warning models for family farms. Wen et al. [26] have investigated and explores the integration of big data technology in the financial sector, specifically focusing on credit risk assessment within the Internet of Things (IoT) framework. Leveraging distributed search engine technology and machine learning algorithms, it customizes web crawlers to gather diverse data related to credit risks from heterogeneous IoT financial sources. For data pre-processing, an inverted table and two-level index files were established in order to facilitate big data analysis using a Spark parallel algorithm. Informed by the scores of financial specialists, the MECE analytical method finds potential quantification and indicators techniques for IoT financial credit risk assessment. In order to create an early

warning system and intelligent credit risk assessment, it mines IoT financial risk data using a multi-level algorithm for spatial association rules and applies the random forest algorithm to feature selection. The research involves IoT finance indicators, undergoes statistical tests using software, and employs factor analysis to interpret the results. With the help of the particle swarm method, the random forest's parameters are optimized, creating a thorough model of financial credit risk assessment that is suitable for the Internet of Things. It is a method to improve credit risk accuracy. Sun et al. [27] have investigated the mining sector has seen listed businesses face severe financial concerns recently due to issues like inadequate spot market liquidity, policy reliance, and protracted investment payback periods. It has been conducted on financial crisis prediction have mostly examined whole sectors, paying little attention to early warning systems and systematic prevention for listed mining firms. A-share mining listed businesses filled the knowledge gap by developing a financial early warning model using a back-propagation neural network. In order to increase financial results, previous study concentrated on alterations in R&D activities and environmental performance. The model demonstrated a high degree of prediction accuracy and financial early warning systems.

A. Background of Recent Research Work

The recent research work reveals that the financial risk management using various methods and aspects. A common limitation lies in the potential lack of generalization, as some models may be overly specialized for specific market conditions, diminishing their effectiveness in diverse financial contexts. The heavy reliance on historical data for training raises concerns about the models' adaptability to dynamic market changes, as unforeseen events may challenge their predictive accuracy. Sensitivity to input features, interpretability challenges, and the risk of overfitting are notable issues, particularly in complex models like deep neural networks. The computational complexity of certain approaches, such as those involving deep learning, may pose obstacles in real-time applications. Assumption violations, lack of explainability, and dependency on training data quality also contribute to the limitations, potentially compromising the reliability of financial risk predictions. The difficulty in handling extreme events or black swan occurrences raises concerns about the models' efficacy in anticipating unforeseen and disruptive financial scenarios. These drawbacks is crucial for refining and enhancing the practical applicability of financial risk warning systems. The above mentioned advantages and disadvantages are motivated me to do this work.

III. PROPOSED METHODOLOGY FOR FINANCIAL RISK MANAGEMENT

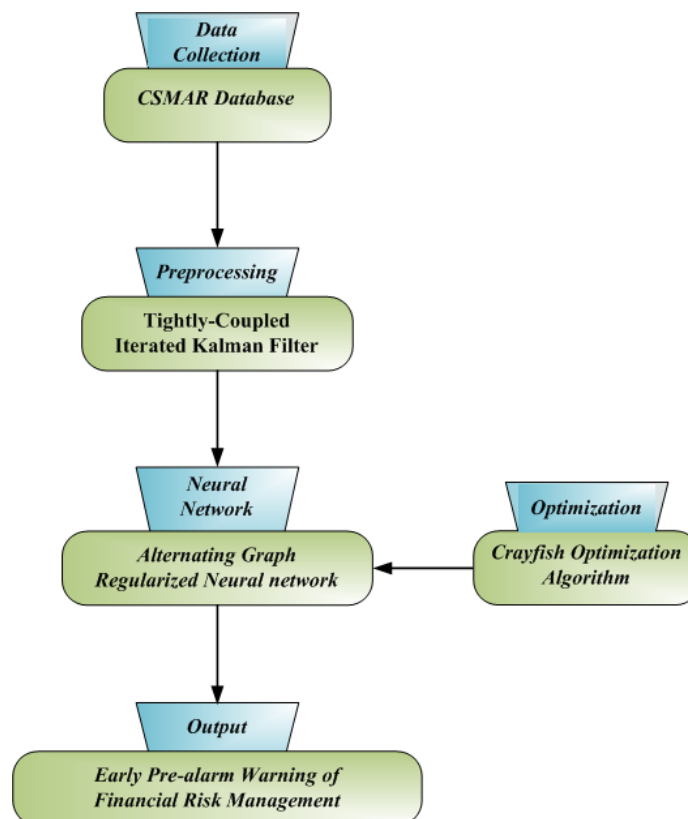


Fig 1: Flowchart of proposed method

A. Data Collection

In this section, data is collected from CSMAR dataset [28].The CSMAR, or China Stock Market & Accounting Research Database, was an extensive platform for research with an emphasis on China's finance and economy. Co., Ltd. Shenzhen CSMAR Data Technology Co. developed it to satisfy the demands of academic research while maintaining compliance with global professional standards and taking into account China's particularities. With the ability to export the retrieved data in formats such as Excel and TXT, users can conduct data queries by choosing data columns from over 4000 tables, a date range, and a corporate code. Fig 1 shows that Flowchart of proposed method

B. Pre-processing for data outlier using Tightly-Coupled Iterated Kalman Filter

In this step, TCIKF is discussed. TCIKF is used to pre-alarm warning of financial risk management [29]. A popular estimate algorithm with a wide range of applications is the TCIKF. Even in cases where measurements are erratic and imprecise, it is intended to estimate the alert warning of financial risk management. Additionally, based on previous financial condition, the Filter forecasts the current financial status. To propose a Tightly-Coupled Iterated Kalman Filter for pre alarm warning for financial risk estimation. The system dynamics can be calculated in equation (1)

$${}^{L_k} p_{jj} = {}^I T_L^{-1} K {}^I T_L {}^{L_j} P_{jj} \tag{1}$$

Where, L_k is the financial pre-alarm body frame at the time. p_{jj} denotes the sampling time of the j^{th} feature point in a financial risk management. L_j, I_j denotes the pre-alarm of FRM frame at the time period. Then, \hat{p}_o the propagation covariance of FRM is determined in (2)

$$\hat{p}_o = \bar{p}_{k-1} \tag{2}$$

Where, \hat{p}_o propagation keeps going till FRM's end time., \bar{p}_{k-1} denotes the propagated state of financial risk management. Then \bar{p}_{k-1} represents the error's covariance between the financial early stage and state propagation of FRM. x state of pre-alarm warning of financial risk management can be determined in equation (3)

$$\bar{x}_k = \hat{x}_k^k, \bar{P}_k = (I - KH)P \tag{3}$$

Where, \bar{x}_k denotes the vector x state of pre-alarm warning of financial risk management. I represents the FRM body frame at the particular time. Then \bar{p}_{k-1} represents the error's covariance between the financial early stage and state propagation of FRM. K denotes the kalman gain of FRM can be determined in (4)

$$K = PH^T (HPH^T + R)^{-1} \tag{4}$$

Where, K denotes the Kalman gain of financial risk management, the state estimation error covariance of financial risk management was denoted as P , then H denotes the measurement matrix of FRM, and then R denotes the pre-alarm measurement covariance of FRM. $HPH^T + R$ denotes the dimension of measurements of the FRM. Then, K new form of kalman gain is obtained in equation (5)

$$K = (H^T R^{-1} H + P^{-1})^{-1} H^T R^{-1} \tag{5}$$

Where, K denotes the Kalman gain of financial risk management. Furthermore, it's crucial to remember that because the financial metrics are impartial, the covariance matrix R^{-1} is diagonal for pre-alarm warning of financial risk management. It helps in pre-alarm warning of financial risk measurements.

C. Financial Risk Management using Alternating Graph-Regularized Neural Network

In this Alternating Graph Regularized Neural Network (AGRNN) is discussed [30]. The AGRNN is used for financial risk management. A graph neural network framework called AGRNN is built block by block using an alternating GCL (Graph Convolutional Network) and GEL (Graph Embedding Layer), with a GCL and a GEL present in every block. The system dynamics can be calculated in equation(6)

$$c(H^{(l)}) = Soft \max(\sigma(H^{(l)}W_c + b)) \tag{6}$$

Where, the W_c denotes the weight matrices of the financial risk management. Then the $c(Z^{(l)})$ denotes the output of the weak FRM of GEL. $H^{(l)}$ represents the output of the FRM of the GCL(Graph Convolutional Network) and GEL (Graph Embedding Layer). $Soft$ denotes the threshold function. C denotes the weak FRM. σ represents the angular function. Weighted embedding of pre-alarm of financial risk management S is explained in equation (7)

$$S = \sum_{l=1}^L (\alpha^{(l)} c(H^{(l)}) + \beta^{(l)} c(z^{(l)})) \tag{7}$$

Here, C denotes the weak FRM. S denotes as the multi-order feature fusion's weighted embedding. $H^{(l)}$ denotes the output of the FRM of the GEL and GCL. $\beta^{(l)}$ denotes the weights FRM of GCL and GEL. Then the $c(Z^{(l)})$ denotes the output of the FRM of GEL. $\alpha^{(l)}$ denotes the weights FRM of GCL and GEL. Error rates of financial risk management $e_z^{(l)}$ was explained in equation (8)

$$e_z^{(l)} = \sum_{i \in \Omega} \pi_i \Pi(c(z^{(l)})_i \neq y_i) / \sum_{i \in \Omega} \pi_i \tag{8}$$

Where, $e_z^{(l)}$ denotes the weight classification error rates. π_i denotes the node weights. $c(Z^{(l)})$ denotes the output of the weak classifier of GEL. Ω denotes the set of samples having supervision information. Weights of FRM for GCL and GEL $\beta^{(l)}$ was determined in equation (9)

$$\beta^{(l)} = \frac{1}{2} \log \frac{1 - e_z^{(l)}}{e_z^{(l)}} + \log(R - 1) \tag{9}$$

Where, η_i denotes the Weight of node update for FRM. R denotes the quantity of classes. $e_z^{(l)}$ denotes the weighted FRM error rates. $\beta^{(l)}$ denotes the pre-alarm of Financial risk management. Then, apply the softmax normalisation to all FRM. η_i thenode weight updating weight for Financial Risk Management can be determined in equation (10)

$$\eta_i = \exp\left(\log\left(\frac{p_{i,r}}{\max(\sum_{j=1, j \neq r}^R p_{i,j,\epsilon})}\right)\right) \tag{10}$$

Where, η_i denotes the Node weight updating weight for FRM. $p_{i,r}$ denotes the probability that the i^{th} sample is in the r^{th} class. ϵ is then a very small value that avoids the divide by zero error. The laplacian matrices L of FRM can be determined in equation (11)

$$L = \sum_{i \in \Omega} \sum_{j=1}^c Y_{ij} \ln S_{ij} \tag{11}$$

Where, L denotes the laplacian matrices. S denotes as the multi-order feature fusion of FRM's weighted embedding. Y denotes the Label information, C denotes the weak classifier. To complete the semi-supervised classification task, all nodes in the training set must then be applied with the weighted node embedding produced by the AGRNN's objective, cross-entropy loss.

D. Optimization of AGRNN using Cray Fish optimization Algorithm

Stepwise process to obtain convergence speed of AGRNN using FHO [31]; Initially, COA creates the uniformly dispersed populace for optimizing the initialization parameters of AGRNN parameters. COA is used to reduce inference time. The global optimization effect and randomness of COA are higher. Then, process of inclusive step given as below,

Step 1: Initialization

Set up the input parameters. In this case, the input parameters are the AGRNN gain parameters, which are represented by η_i

Step 2: Random Generation

After initialization, the COA generates the mechanism of moving towards the Crayfish Optimizer using input parameters chosen at random. The system dynamics can be calculated in equation (12)

$$X = [X_1, X_2, \dots, X_N] = \begin{bmatrix} X_{1,1} \cdots X_{1,j} \cdots X_{1,dim} \\ \vdots \quad \cdots \quad \vdots \quad \cdots \quad \vdots \\ X_{i,1} \cdots X_{i,j} \cdots X_{i,dim} \\ \vdots \quad \cdots \quad \vdots \quad \cdots \quad \vdots \\ X_{N,1} \cdots X_{N,j} \cdots X_{N,dim} \end{bmatrix}$$

(12)

$X_{i,j}$ indicated the location of individual i in the j dimension, N indicates the number of populations, and X indicates the beginning population position. It happens at random that crayfish compete for caverns. The crayfish enters the cave directly for summer vacation, indicating that there was no competition for caves.

Step 3: Fitness Function

The random answer and initialized judgments yield the outcome. The evaluation of fitness function makes use of the effects of weight parameter optimization.

$$fitness\ function = Optimizing [\eta_i] \tag{13}$$

Where, η_i denotes the Node weight updating for pre-alarm warning for Financial Risk Management.

Step 4: Exploration Phase

The crayfish food intake augmentation algorithm's unpredictability. COA will become closer to the ideal solution during the foraging stage, improving the algorithm's exploitation and convergence capabilities. The system dynamics can be explained in (14)

$$X_{i,j} = lb_j + (ub_j - lb_j) * rand \tag{14}$$

Where, lb_j denotes the lower bound of the j^{th} dimension, ub_j denotes the upper bound of the j^{th} dimension, and $rand$ denotes a random number. $X_{i,j}$ denotes the position of individual i in the j dimension. COA draws inspiration from the foraging, summertime vacation, and competitive nature of crayfish. The COA's exploration stage is the summer resort stage, while the exploitation stages are the foraging and competition stages. Then, p is obtained by equation (15)

$$p = C_1 * \left(\frac{1}{\sqrt{2 * \pi * \sigma}} * \exp\left(\frac{-(temp - \mu)^2}{2\sigma^2}\right) \right) \tag{15}$$

Where, $temp$ denotes the crayfish algorithm's environment's temperature. C_1 denotes to regulate the intake according to various temperatures. σ denotes to regulate the intake according to varying temperatures. μ represents to the temperature most suitable for it. The competitive nature of crayfish and their summertime vacations serve as inspiration for COA. The COA's exploration stage is the summer resort stage, while the exploitation stages are the foraging and competition stages.

Step 5: Exploitation Phase for optimizing e_z

The crayfish represents the best course of action and is moving into the cave in order to accelerate convergence. In addition to bringing people closer to the best answer, being close to the cave increases COA's exploitation potential and speeds up the algorithm's convergence. The dynamics of the system can be understood in (16).

$$X_{i,j} = X_{i,j}^t + C_2 * rand * (X_{shade} - X_{i,j}) \tag{16}$$

Where, $X_{i,j}$ denotes the position of individual i in the j dimension, t represents the current iteration number, and $t+1$ represents the next iteration number of the generation, C_2 is a decreasing curve. $rand$ denotes a random number. X_{shade} represents the cave position of the crayfish. z represents the random individual of crayfish can be determined in equation (17)

$$z = round(rand * (N - 1)) + 1 \tag{17}$$

Where, z is crayfish engage in rivalry with one another in the competition stage. X_i adjusts their position based on X_z , $rand$ denotes a random number. N represents the number of population. When hunting, claw fish typically grab huge prey and break it up before delivering it to their second and third walking foot to grasp and chew on. Use for little foods the right and left walking foot to grasp and gnaw on. Following a hunt, they frequently dive behind cover or use pincers to keep other crayfish from robbing them.

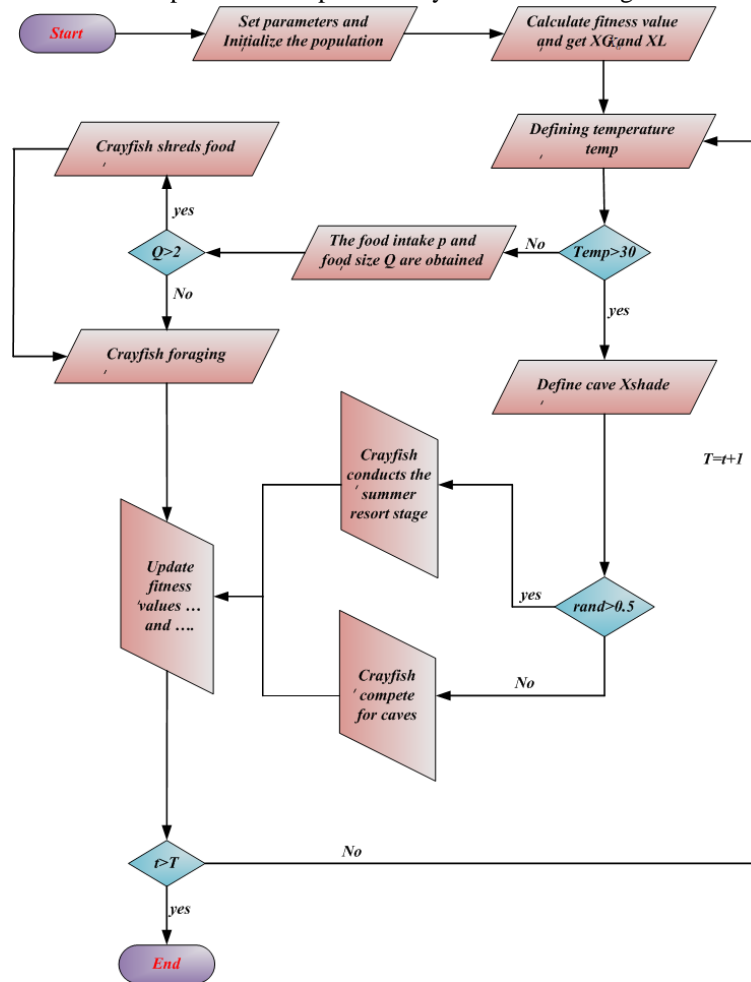


Fig 2: Flow chart of Cray Fish optimization algorithm

Step 6: Termination Criteria

Finally, COA optimizes the factor iteratively repeat till it reaches halting criteria. AGRNN effectively gives how to maintain financial risk management. Finally, the proposed FRM-AGRNN-COA found out the procedures for maintaining the financial management. Check the end criteria, and the process is complete if the best result is achieved; if not, move on to step 3. Fig 2 illustrates the Flow chart of Crayfish Optimization Algorithm.

IV. RESULT AND DISCUSSION

In this section a hybrid AGRNN-COA technique for financial risk management is presented in this research. The hybrid technique that has been suggested combines the capabilities of the Alternating Graph-Regularized Neural Network (AGRNN) and Crayfish Optimization Algorithm (COA). It is usually referred to as the AGRNN-COA approach. The primary goal of the suggested technique is to maintain the financial risk at a particular time.

Analysis the Relative Distance at different serial number is shown in fig 3. The relative distance values varied between 0 to 250 during the serial number initiated from 0 to 50000. Analysis the Assessment Result at different sample set is shown in fig 4. The assessment values varied between 0.90 to 0.70 during the sample set initiated from 0 to 820. Fig 5.Subplot (a) shows the relationship between classification accuracy with varying node counts. The classification accuracy is varied from 70 to 90 during the number of nodes initiated from 0 to 6000. Subplot (b) shows the relationship between classification accuracy with varying node counts. The classification accuracy is varied from 62 to 82 during the number of nodes initiated from 0 to 6000.

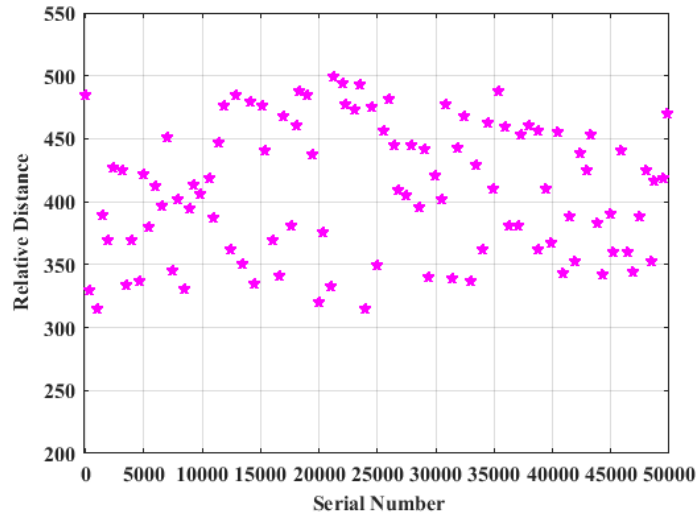


Fig 3: Analysis of Relative Distance at different serial number.

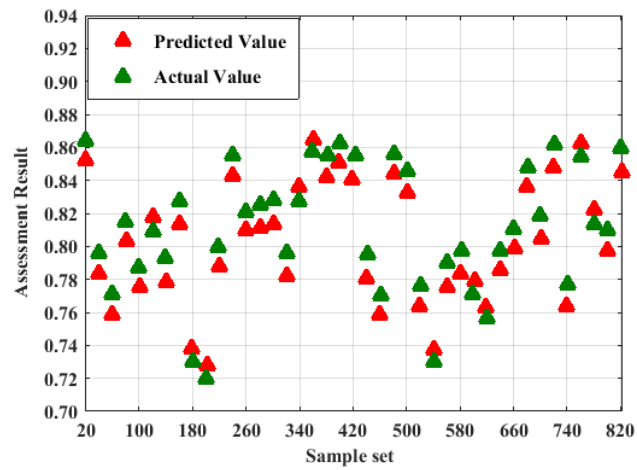


Fig 4: Analysis of Assessment result at different sample set.

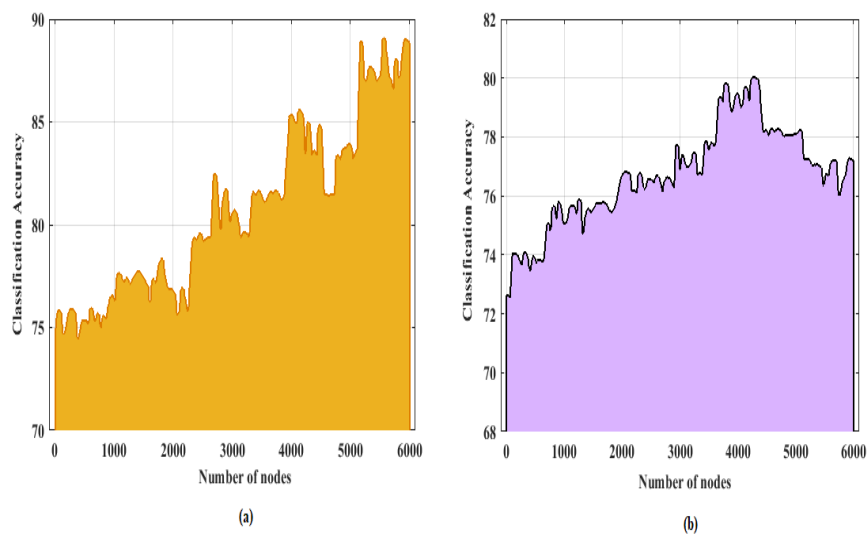


Fig 5: Analysis of (a) and (b) Classification Accuracy at different number of nodes.

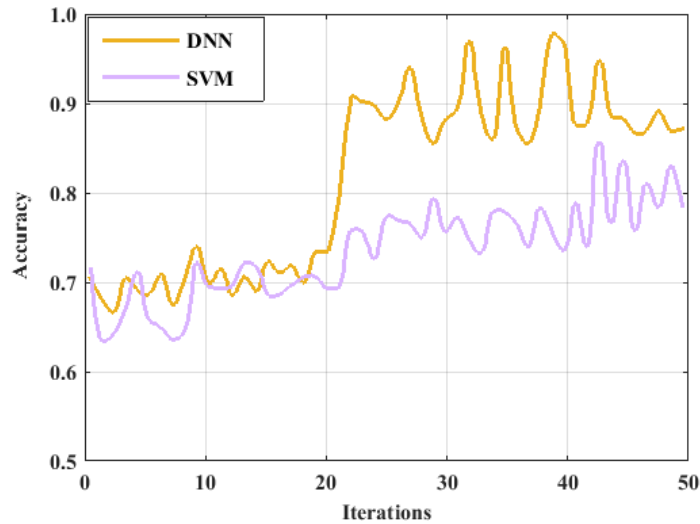


Fig 6: Analysis of Accuracy at different Iterations.

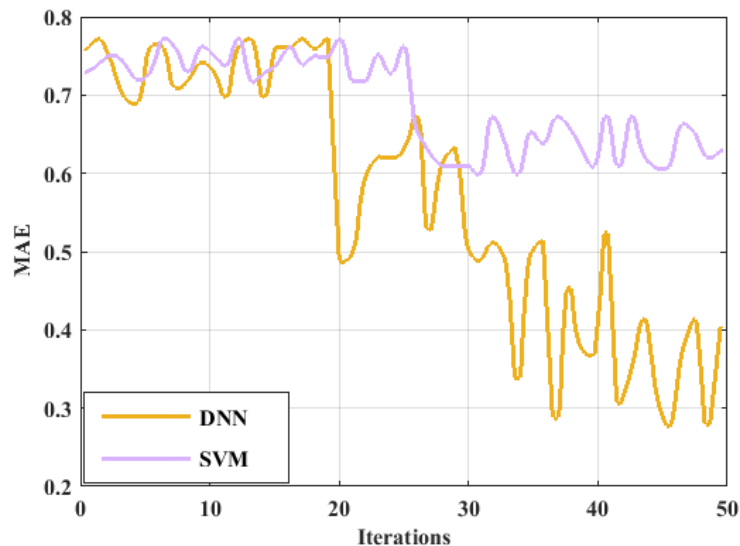


Fig 7: Analysis of MAE at different Iterations.

Fig 6 depicts the analysis of accuracy at different iterations. Here, the accuracy is compared between DNN and SVM. The DNN attains 0.98 when the iteration value is 50. The SVM attains 0.8 when the iteration value is 50. The accuracy of DNN is higher than SVM. Fig 7 depicts the analysis of MAE at different iterations. Here, the MAE is compared between DNN and SVM. The DNN attains 0.75 when the iteration value is 0. Then, the DNN decreases and falls to 0.4 during the iteration is 50. The SVM attains 0.78 when the iteration value is 0. Then, the SVM decreases and falls to 0.62 during the iteration is 50.

A. Performance measures

This section describes the proposed approach's performance in light of the simulation's results. To estimate the technique for financial risk management system, in this paper utilize the hybrid FRM-AGRNN-COA approach. The objective of the proposed method helps in financial risk management. Performance measures like accuracy, error rate, F-score, precision, recall, computation time, ROC, sensitivity, and specificity are analyzed to assess the performance.

1) Accuracy

It is the ratio of count of exact prediction with total number of predictions made for a dataset. It is measured by following equation (18),

$$Accuracy = \frac{(TP+TN)}{(TP+FP+TN+FN)} \tag{18}$$

2) *Computational time*

The execution time of an algorithm can only be determined by its temporal complexity, which is totally reliant on the algorithm and its inputs. The computational complexity indicates how long an algorithm takes to run. This is scaled by equation (19)

$$CPU\ Time = IC * CPI / Clockrate$$

(19)

3) *ROC*

Equation (20) provides the ratio of the erroneous negative to the genuine positive area.

$$ROC = 0.5 \times \left(\frac{TP}{TP + FN} + \frac{TN}{TN + FP} \right)$$

4) *Precision*

Precision, or how well the model generates positive predictions, is one indicator of a machine learning model's efficacy. Precision is determined by dividing the total number of positive predictions by the number of true positives, as indicated in equation (21).

$$Precision = \frac{TP}{TP + FP}$$

5) *Recall*

The percentage of data samples that a machine learning model correctly identifies as being in a class of interest is known as the true positive rate (TPR), also known as recall. It is measured by following equation (22).

$$Recall = \frac{TP}{TP + FN}$$

6) *F-Score*

A machine learning model's performance is assessed using a metric called the F-score. As seen in equation (23), it combines recall and precision into a single score.

$$F - Score = 2 * \frac{precision * recall}{precision + recall}$$

7) *Error Rate*

One less than accuracy is the error rate. A model with a 90% accuracy rate would have a 10% mistake rate. Formula (24) is used to calculate it.

$$ErrorRate = 1 - \frac{FP + FN}{TP + TN + FP + FN}$$

8) *Sensitivity*

The measure that assesses a model's capacity to forecast true positives for every possible category is called sensitivity. Any categorical model can use these measures. Equation (25) provides it.

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

9) *Specificity*

One measure used to assess a model's predictive power for true negatives in each accessible category is called specificity. You can use these metrics with any categorical model. Equation (26) has the information.

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

B. Performance Analysis

Figure 8 to 11 depicts simulation results of proposed FRM-AGRNN-COA method. Then the proposed FRM-AGRNN-COA method is likened to existing Heap Based Optimization (FRM-HBO), Deep Neural Network (FRM-DNN) and Supervised Algorithm (FRM-SVM) methods.

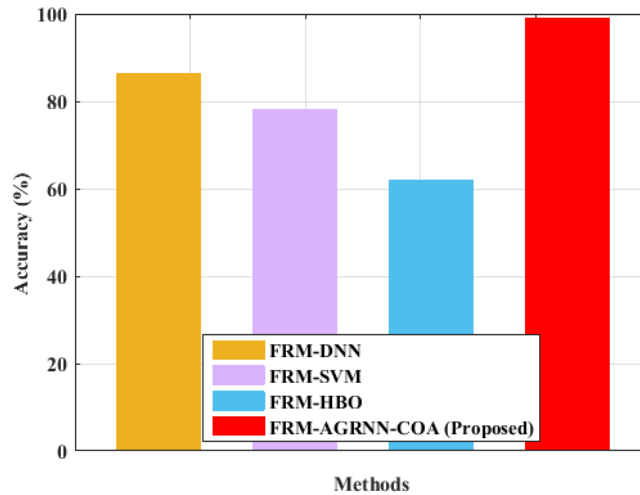


Fig 8: Comparison of proposed method accuracy with existing methods

Fig 8 depicts the Comparison of proposed method Accuracy with existing methods. The accuracy of FRM-SVM is 78% and the accuracy of FRM-DNN is 83% and the accuracy of FRM-HBO is 62%. Then the accuracy of proposed method FRM-AGRNN-COA is 99%. It shows that the proposed method have better accuracy than FRM-SVM, FRM-HBO and FRM-DNN.

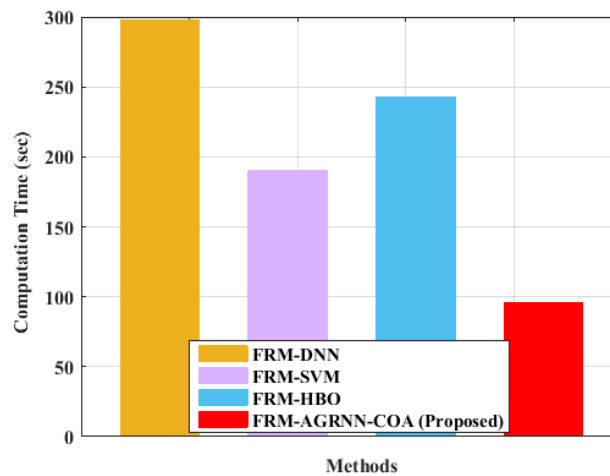


Fig 9: Comparison of proposed method Computation time with existing methods

Fig 9 depicts the comparison of proposed method computation time with existing methods. The computation time of FRM-DNN is 295 sec and the computation time of FRM-SVM is 180 sec and the computation time of FRM-HBO is 240 sec. Then the computation time of proposed method FRM-AGRNN-COA is 90 sec. It shows that the proposed method have efficient computation time than FRM-HBO, FRM-SVM and FRM-DNN.

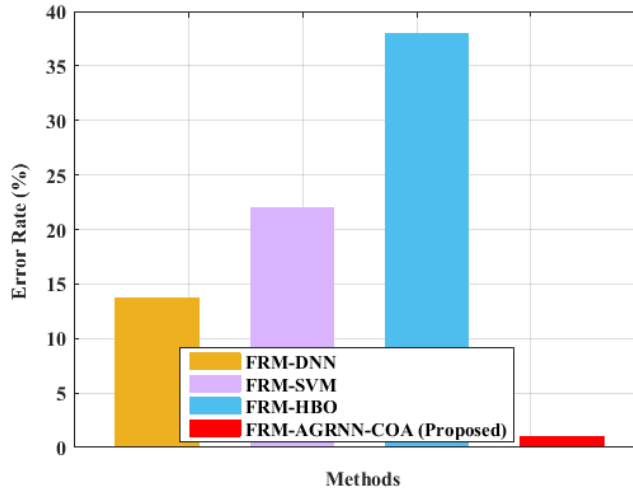


Fig 10: Comparison of proposed method error rate with existing methods

Fig 10 depicts the Comparison of proposed method error rate with existing methods. The error rate of FRM-DNN is 14% and the error rate of FRM-SVM is 22% and the error rate of FRM-HBO is 38%. Then the error rate of proposed method FRM-AGRNN-COA is 1.5%. It shows that the proposed method have lower error rate than FRM-SVM, FRM-HBO and FRM-DNN.

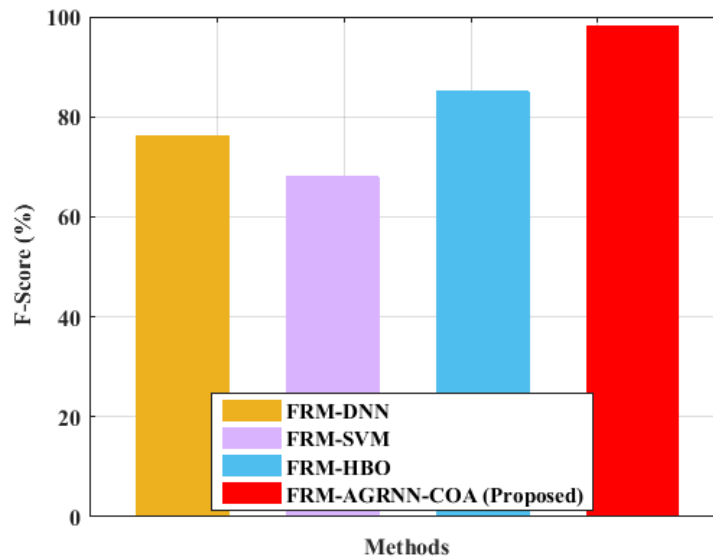


Fig 11: Comparison of proposed method F-Score with existing methods

Fig 11 depicts the Comparison of proposed method F-Score with existing methods. The F-Score of FRM-DNN is 75% and the F-Score of FRM-SVM is 65% and the F-Score of FRM-HBO is 82%. Then the F-Score of proposed method FRM-AGRNN-COA is 99%. It shows that the proposed method have better F-Score than FRM-SVM, FRM-HBO and FRM-DNN.

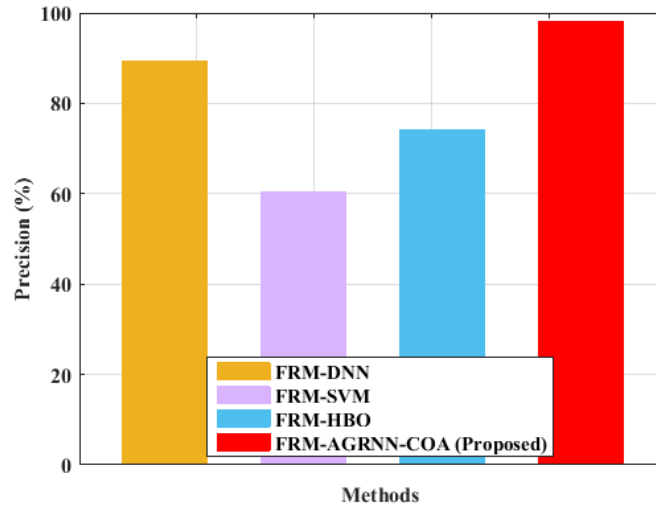


Fig 12: Comparison of proposed method precision with existing methods

Fig 12 depicts the Comparison of proposed method precision with existing methods. The precision of FRM-DNN is 90% and the precision of FRM-SVM is 60% and the precision of FRM-HBO is 76%. Then the precision of proposed method FRM-AGRNN-COA is 98%. It shows that the proposed method has better precision than FRM-SVM, FRM-HBO and FRM-DNN.

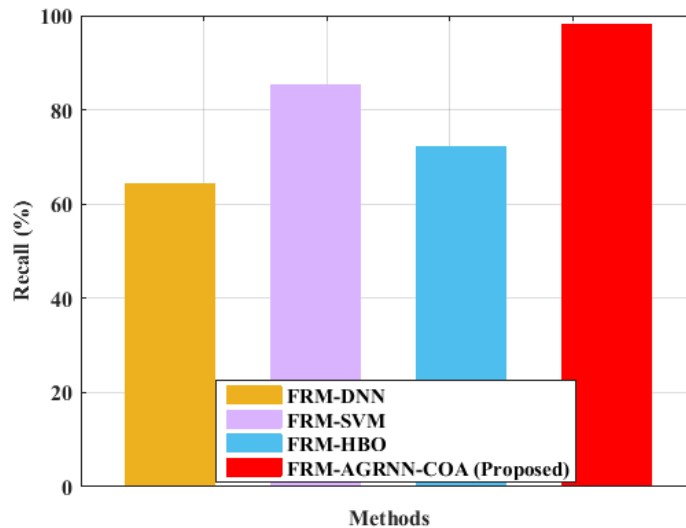


Fig 13: Comparison of proposed method recall with existing methods

Fig 13 depicts the Comparison of proposed method recall with existing methods. The recall of FRM-DNN is 62% and the recall of FRM-SVM is 83% and the recall of FRM-HBO is 72%. Then the recall of proposed method FRM-AGRNN-COA is 99%. It shows that the proposed method has better recall than FRM-SVM, FRM-HBO and FRM-DNN.

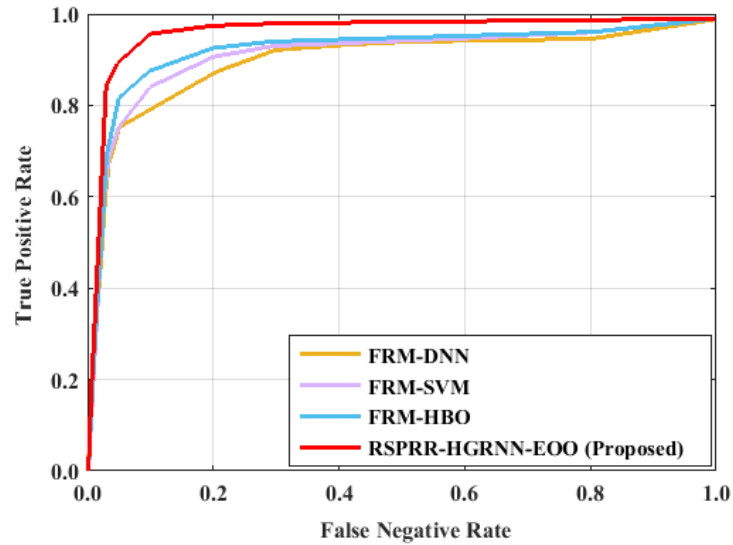


Fig 14: Comparison of proposed method ROC with existing methods

Fig 14 depicts the Comparison of proposed method ROC with existing methods. The ROC of FRM-DNN is 0.9 attains at 0.3 false negative rate and the ROC of FRM-SVM is 0.9 attains at 0.3 false negative rate and the ROC of FRM-HBO is 0.9 attains at 0.3 false negative rate. Then the ROC of proposed method FRM-AGRNN-COA is 0.95 attains at 0.1 false negative rate. It shows that the proposed method have better ROC than FRM-SVM, FRM-HBO and FRM-DNN.

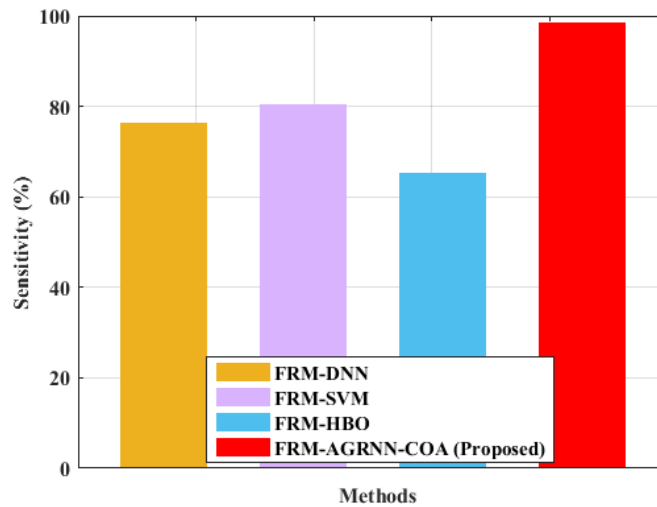


Fig 15: Comparison of proposed method sensitivity with existing methods

Fig 15 depicts the Comparison of proposed method sensitivity with existing methods. The sensitivity of FRM-DNN is 78% and the sensitivity of FRM-SVM is 80% and the sensitivity of FRM-HBO is 63%. Then the sensitivity of proposed method FRM-AGRNN-COA is 98%. It shows that the proposed method have better sensitivity than FRM-HBO, FRM-SVM and FRM-DNN.

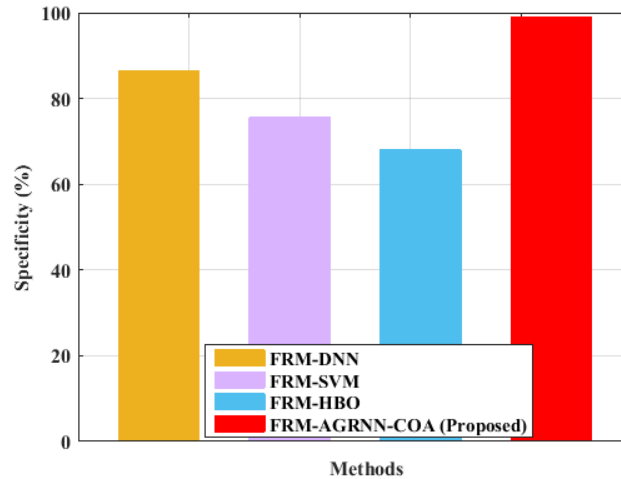


Fig 16: Comparison of proposed method specificity with existing methods

Fig 16 depicts the Comparison of proposed method specificity with existing methods. The specificity of FRM-DNN is 84% and the specificity of FRM-SVM is 76% and the specificity of FRM-HBO is 69%. Then the specificity of proposed method FRM-AGRNN-COA is 99%. It shows that the proposed method have better specificity than FRM-SVM, FRM-HBO and FRM-DNN.

V. CONCLUSION

This study is used to improve the financial risk management using the AGRNN-COA approach. It gives early warning of financial risk management. The proposed method is assessed using the MATLAB Simulink platform and contrasted with various alternative approaches that are currently in use. A wide range of scenarios, such as random and optimal scheduling and a complex COA algorithm, are employed to assess the proposed method. The outcome indicates that, in comparison to existing methods, the proposed approach's based error is smaller. The goal of the proposed model is to improve and early warning of financial risk management system. In spite of variations in the object's moment of inertia, the controller keeps the nature of its response constant. Also, it helps in early warning of FRM. The result shows that compared to existing methodologies, the based error of the proposed strategy is smaller. The result shows that the accuracy level of proposed FRM-AGRNN-COA approach is 98% that is higher than the other existing methods. The proposed FRM-AGRNN-COA method has an F-score of 97% and a specificity of 99%. The error rate of the proposed FRM-AGRNN-COA approach is 1.8%, which is very less compared to other existing techniques. From the result, it is concluded that the proposed approach based financial risk management system is accurate compared to existing techniques. The proposed framework aims to provide early warning for managing financial risk. The proposed method performs significantly better than the other optimization options, according to the results.

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