J. Electrical Systems 20-7s (2024): 3016-3030

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Construction and Application of Financial Risk Early Warning Model based on Machine Learning

Journal of Electrical Systems

Abstract: - In today's financial environment, listed corporations face increasingly complicated markets and volatile financial risks. The corporations realize the critical significance of financial risk management in the long-term development of their businesses. The difficulty is that market conditions change frequently, and existing methodologies make it impossible to identify risks in a timely and reliable manner. In order to prevent losses in the future and maintain the financial health of the organisation, it is now essential to improve the timeliness and accuracy of financial risk prediction. In this manuscript Construction and Application of Financial Risk Early Warning Model based on Machine Learning (CSN-FREWM-ML-AIDINN) is proposed. Market data, Financial statements and financial risk event data are the first sources of data gathered. The gathered data are then put into pre-processing. In pre-processing, Innovation Saturated Koopman Kalman Filter (ISKKF) is used for normalization the data. After pre-processing the output is fed to Anti-Interference Dynamic Integral Neural Network (AIDINN) for predicting the financial risk. Typically, the AIDINN predictor does not provide ways for optimising parameters to guarantee precise financial risk prediction. Hence, proposed Red Panda Optimization Algorithm (RPOA) enhances AIDINN, accurately predict the financial risk. The proposed method is implemented in python version and efficacy of the CSN-FREWM-ML-AIDINN technique is assessed with support of numerous performances like f1-score, recall, Root mean square error, accuracy, Error rate, Index of error, profitability and Development capacity are analysed. The performance of the proposed CSN-FREWM-ML-AIDINN approach contain 22.36%, 25.42% and 18.17%high accuracy; 21.26%, 15.42% and 19.27% high precision and 25.29%, 28.36% and 28.55% low error rate when analysed to the existing methods like Financial Risk Early Warning Model for Listed Companies Using BP Neural Network and Rough Set Theory (FREWM-LC-BPNN), Financial Risk Early Warning Based on Wireless Network Communication and the Optimal Fuzzy SVM Artificial Intelligence Model (FREW-WNC-PNN) , An Early Control Algorithm of Corporate Financial Risk Using Artificial Neural Networks (ECAC-FR-ANN) methods respectively.

Keywords: Stock Market Dataset, Innovation Saturated Koopman Kalman Filter, Red Panda Optimization Algorithm and Financial risk Anti-Interference Dynamic Integral Neural Network .

I. INTRODUCTION

Financial risk management has become more and more important for listed companies as the world's financial markets continue to change and get more complex. Financial risk includes all of the unknowns that can arise in a business's operations, including changes in the market, problems with liquidity, and shifts in the economic cycle, and more [1,2]. Traditional financial risk prediction approaches face various obstacles in this dynamic and complicated environment. These traditional methods frequently fall short in providing accurate, complete estimates of financial risk because they do not fully take these aspects into account. A company's financial risk is also greatly impacted by the increasing unpredictability elements in the financial markets, such as strained international relations, policy changes, natural disasters, and others. Conventional approaches frequently show fragility when dealing with these variables of uncertainty and find it difficult to adjust successfully to the market's dynamic fluctuations [3-6].An essential instrument in the toolbox of financial institutions and regulatory agencies, a FREWM is intended to anticipate and mitigate potential risks in the financial environment. Its basis is painstaking data gathering and analysis, utilizing a wide range of sources to identify patterns and trends suggestive of impending dangers. It sorts through enormous information using advanced analytical approaches like statistical modeling and machine learning to identify a variety of hazards, such as credit, market, liquidity, operational, and systemic issues [7-9]. The actual power of FREWM is found in its ability to not only recognize hazards but also to send out early warning signals, which notify relevant parties about new threats either instantly or with enough time to take preventative action. These indicators point institutions and regulators in the direction of proactive risk management techniques [10, 11]. They can take many different forms, from sudden changes in asset values to declining credit quality. Furthermore, FREWM makes scenario analysis and stress testing easier, giving stakeholders a better understanding of how resilient

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financial institutions and markets are in challenging circumstances. It helps assess possible effects on asset portfolios, capital sufficiency, and overall financial stability by modeling hypothetical situations [12, 13].

It guarantees its precision, dependability, and flexibility in response to changing market circumstances by means of stringent validation, calibration, and on-going observation [14]. It offers useful insights and recommendations to decision-makers that guide the formulation of regulations and resource allocation to fortify the financial system against future shocks. It is essentially a proactive approach to risk management, encouraging a vigilant, resilient, and adaptable culture throughout the financial ecosystem [15].

Despite its limitations, the research provides insightful information about financial risk prediction for public firms. First of all, the dataset may be too homogeneous and out-dated to allow the model to adjust to changing market conditions and industry trends. In addition, even if it incorporates market and financial data in a thorough manner, it could miss some risk variables that are unique to particular settings or businesses. Furthermore, even with the use of sophisticated analytical methods, the model's interpretability continues to be problematic, which hinders stakeholders' confidence and comprehension [16, 17]. Finally, the research's restricted focus on particular methodology prevents consideration of other strategies that can improve model performance. Even while businesses understand how important financial risk management is to achieving sustainable development, they still find it difficult to foresee hazards with enough accuracy and time when utilizing traditional approaches [18, 19].

This research presents a new approach for forecasting financial risks for publicly traded firms. In order to improve accuracy and timeliness, it focuses on finding relevant financial indicators and market aspects that are essential for risk assessment. It guarantees a thorough investigation of risk elements by utilizing a comprehensive dataset that includes market data, financial risk event data and financial statements. A Dynamic Integral Neural Network (DINN) has considerable advantages since it adapts its structure and parameters dynamically during training, allowing it to better handle complicated and shifting input patterns. This adaptability allows DINNs to perform more accurately and efficiently in tasks that involve non-stationary data or where the relationships between inputs and outputs change over time. This research aims to investigate which method is more effective in predicting the accurate financial risk.

Below is a summary of this research work's principal contributions.

- In this research, CSN-FREWM-ML-AIDINN is proposed.
- Develop Innovation Saturated Koopman Kalman Filter (ISKKF) based pre-processing method for data normalization.
- AIDINN is constructed for the prediction of financial risk.
- The proposed model's efficiency is analysed with the existing methods like FREWM-LC-BPNN, ECAC-FR-ANN and FREW-WNC-PNN models respectively.

The remaining manuscripts are arranged as follows: The literature review is reviewed in Part 2, the technique is explained in Part 3, the results are verified in Part 4, and the article is concluded in Part 5.

II. LITERATURE SURVEY

Several works have presented previously in literatures were depending on the financial risk prediction using deep learning. Few of them were mentioned here,

Liu and Yang. [20] have presented FREWM-LC-BPNN. In modern financial environment, listed corporations face increasingly complicated markets and volatile financial risks. Financial risk management has become more and more important for listed companies as the world's financial markets continue to change and get more complex. The corporations realize the critical significance of FRM in the long-term development of their businesses. The difficulty was that market conditions change frequently, and existing methodologies make it impossible to identify risks in a timely and reliable manner. Therefore, improving financial risk prediction's timeliness and accuracy has become essential in the present field in order to prevent losses and maintain the financial stability of the organisation. It attains high accuracy and high error rate.

Li. [21] has presented ECAC-FR-ANN. As China's economy grows, firms face increasingly difficult business environments. The economic downturn has led to an increase in corporate troubles and insolvency due to financial difficulties. A number of things will happen as a result of the business's financial issues, endangering creditors, investors, and financial investors. Financial risk refers to the unpredictability of capital gains from debt management and the risks associated with using debt funds for leverage. Essentially, financial risk was the likelihood that nonproduction and operational operations like capital recovery, distribution, fund-raising, and investment will cause financial losses within a given range and over a given time period as a result of both internal and external factors that were unpredictable. It attains high profitability and low accuracy.

Ma et al. [22] have presented FREW-WNC-PNN .Risky occurrences like the global economic crisis have happened since the turn of the century and have had a significant impact on the nation's actual economy. In order to assist and promote the growth of medium - and small -sized listed enterprises, the state has actively promoted inclusive finance in recent years and formed financing guarantee companies for them. A network that has been set up utilizing wireless communication technologies was called a wireless network. It consists of radio frequency technology and infrared technology tailored for short-distance wireless connections, as well as global voice and data networks that enable users to create wireless connections across vast distances. Many medium - and small -sized listed companies were greatly impacted by these occurrences, which leads to a high number of bankruptcies among them. Indeed, a major contributing factor to the regular bankruptcy of medium - and small - sized listed companies was the general lack of knowledge on risk mitigation and efficient early warning systems for financial risks. It attains high development capacity and high error rate.

Song and Wu.[23] have presented “The Impact of Financial Enterprises’ Excessive Financialization Risk Assessment for Risk Control based on Data Mining and Machine Learning”. Growing numbers of businesses were participating in the financial market as a result of the global economy's recent expansion, which supports the long-term growth of the domestic economy. Nonetheless, the subsequent issues include financial market volatility, mismanagement, commercial fraud, and the breakup of numerous company capital chains as a result of inadequate risk knowledge. Due to their inability to withstand risk, small businesses were in danger of going bankrupt. This was mostly because more small businesses were choosing to focus more on virtual financial markets than on real economic investments. It attains low Index of error and low development capacity.

Zhang and Hu. [24] have presented “Early Warning of Financial and Business Management Based on Three Improved BP-NN Algorithms”. Businesses will encounter numerous difficulties in today's globe as the economic climate continues to advance, and financial concerns have long been a significant source of corporate uncertainty. As the industry develops, it was dealing with additional risks and difficulties. The prevention of financial crises was a major business concern. According to research on the financial crisis warning system that has been done thus far, financial market research was the first step in the system's creation. Simultaneously, there was a need for tighter financial crisis early warning and management protocols, more integration of business management processes, and robust support for forecasting models and forecasting technology. Businesses can improve their financial management by using early, successful, and economical financial reporting. It attains high recall and low f1-score.

Lyu. [25] have presented “Construction of Enterprise Financial Early Warning Model Based on Logistic Regression and BP Neural Network”. The number of Chinese companies going through financial crises has dramatically increased recently, and these companies' overall risk tolerance was low. ‘Thus, in order to identify the warning indicators of a corporate financial crisis, it was imperative to set up an early warning system. The way to get rid of buried threats corporate financial crisis before it occurs and to notify managers beforehand, allowing for the prompt implementation of appropriate actions’. Since the Chinese economy has risen so quickly, small and medium-sized businesses China's most important group have played a significant role in the country's GDP growth, employment prospects, and foreign export commerce. It attains high f1-score and high Index of error.

Min et al. [26] have presented “Automotive manufacturing enterprise financial risk evaluation monitoring and early warning simulation: based on the perspective of value chain analysis”. The made in China 2025 initiative has made it abundantly evident that the automobile sector was one of the keystones of the state economy. It has been driving supply-side reform, advancing real economy development, and progressing up the value chain. China's car industry has advanced significantly over the thirty years that the "Market for Technology" policy was in place. Nonetheless, a number of issues with Chinese car manufacture stand out, including excessive administrative costs, rising production but falling profit, high levels of inventory, and a lack of key technologies. In a constantly shifting economic landscape, certain vehicle manufacturing companies, particularly those with smaller operations, were confronted with mounting financial concerns and potentially even a financial crisis. It attains high recall and high RMSE.

III. PROPOSED METHODOLOGY

The proposed CSN-FREWM-ML-AIDINN is addressed in this segment. This segment presents the a precise explanation of the research approach use in financial risk in early warning model. The important need for accurate and rapid financial risk prediction for publicly traded corporations in dynamic markets. It takes a holistic strategy. Initially, it compiles a large dataset that includes market data, financial statements, and financial risk event records. Following that, itbuilds a Financial Risk Early Warning Model with an Anti-Interference Dynamic Integral Neural Network (AIDINN), taking use of its ability to detect complicated data patterns. This model is painstakingly trained and optimized with historical data. To demonstrate its efficacy, it run cross-validation on the model and compares its performance to established methods. The block diagram of CSN-FREWM-ML-AIDINN is represented in Figure 1. This approach consists of the following steps: pre-processing, prediction, optimisation, and dataset. Thus, the detailed description about CSN-FREWM-ML-AIDINN is given below,

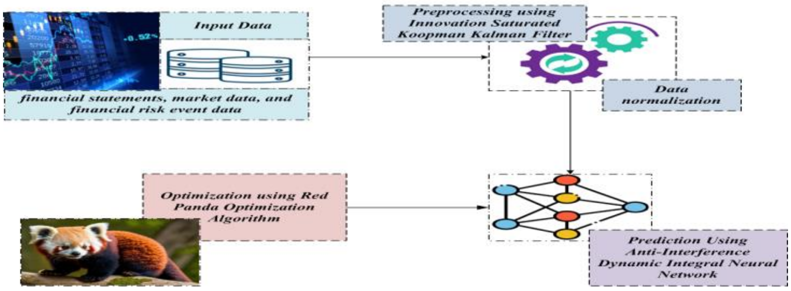

Figure 1: The proposed CSN-FREWM-ML block diagram

A. Data Acquisition

In this section, input data is collected from market data, , financial statements, and financial risk event data[21]. “In the third quarter of 2022, 88 financial sector businesses from the Shenzhen and Shanghai stock exchanges are examined in this research. Fifty five samples were used for training and thirty three for testing. This model is based on financial data from these companies from 2012 to 2022”. This project intends to increase the accuracy of financial risk prediction for listed firms by implementing an effective warning model. Data sources used in research include financial statements, market data, and financial risk events. The dataset employed in this study has limitations, particularly in terms of time and industry.

B. Pre-Processing using Innovation Saturated Koopman Kalman Filter (ISKKF)

In this section, Innovation Saturated Koopman Kalman Filter (ISKKF) is discussed [27].Data pre-processing is crucial for inconsistencies are removed, and raw data is converted into relevant information that can be efficiently managed. ISKKF method is used for data normalization. Simply overloading the innovations, ISKKF outperforms conventional Kalman filtering techniques, resulting in more precise state variable estimation and lower estimate errors. This improved filtering accuracy is especially important for financial risk prediction, where even tiny mistakes can have major repercussions. In financial risk prediction, ISKKF's main objective is to offer early alerts for impending market disruptions, crises, or other unfavourable occurrences. Through precise financial data filtering and signal identification, ISKKF can notify stakeholders of new hazards before they become significant problems.

$$E_k = zm_k - h(\tilde{x}_k) \tag{1}$$

Where E_k represents the innovation, zm_k denotes the measurement of each node and $h(\tilde{x}_k)$ represents the measurement vector that is anticipated.

$$\tilde{z}_k = Az_k + K_k \cdot sat_\sigma\left(zm_k - C^h z_k\right) \tag{2}$$

Where $\tilde{z}_k$ denotes the predicted state vector, A, C^h denotes the Koopman observer form coefficient matrices, z_k denotes the state vector, K_k represents the KF gain matrix, sat_σ represents the saturation function, zm_k denotes the measurement of each node and $C^h z_k$ denotes the system state quality.

$$\tilde{z}_k = A\hat{z}_{k-1} \tag{3}$$

Where $\tilde{z}_k$ denotes the predicted state vector, A denotes the coefficient matrices of Koopman observer form and $\hat{z}_{k-1}$ denotes the filtered state vector. Data normalization is expressed in equation (4)

$$\tilde{P}_k = A\hat{P}_{k-1}A^T + Q_k \tag{4}$$

Where $\tilde{P}_k$ represents the predicted state covariance matrix, A denotes the coefficient matrices of Koopman observer form, $\hat{P}_{k-1}$ represents the filtered state covariance matrix and Q_k denotes the noise vector.

$$\hat{P}_k = \tilde{P}_k - K_k\left[P_{zz} + R\right]K_k^T \tag{5}$$

Where $\tilde{P}_k$ represents the predicted state covariance matrix, K_k represents the KF gain matrix, $\hat{P}_k$ represents the filtered state covariance matrix, , R denotes the state transition function, P_{zz} represents the innovation covariance matrix and K_k^T represents the KF gain matrix with time T . Finally the ISKKF is normalized the data. Then the preprocessed data is fed to prediction process

C. Prediction of Financial Risk Using Anti-Interference Dynamic Integral Neural Network (AIDINN)

In this segment, Prediction of Financial Risk using Anti-Interference Dynamic Integral Neural Network (AIDINN) is discussed [28].AIDINN is built to dynamically adjust to shifting risk variables and market conditions. Its capacity to immediately change its structures and parameters ensures that the model continues to be applicable and useful even in uncertain settings Early warning of potential financial dangers is one of AIDINN's main objectives. The model's ability to identify tiny signals and trends in data allows it to warn stakeholders of new threats before they become serious emergencies. One of the AIDINN's main advantages is its capacity to reduce interference from outside sources that could skew the model's predictions.

$$\iota(t) = \begin{cases} \iota(t-T) + \phi\varepsilon(t) & t \ge T \\ 0 & 0 < t < T \end{cases} \tag{6}$$

Here , $\phi\varepsilon(t)$ represents the parameter of positive error function, T denotes the period of Triangular wave movement and t represents the time variable.

$$\Delta\eta(t) = \frac{\lambda}{T} \cdot \left(d - \frac{2}{T}\right) \tag{7}$$

Where $\Delta\eta(t)$ represents the scalar function with time variable, λ denotes the slope of the Triangular wave movement, d represents the remainder of t divided by T , T denotes the period of Triangular wave movement and t represents the time variable.

$$\Delta\eta(t) = \kappa\cos(\upsilon_0 t) \tag{8}$$

Where $\Delta\eta(t)$ represents the scalar function with time variable, $\upsilon_0 t$ denotes the frequency of the cosine wave movement and κ represents the amplitude of the cosine wave movement. The Financial Risk is predicted in equation (9)

$$\overline{E}(t) = -\alpha\rho(E(t)) \tag{9}$$

Here $\overline{E}(t)$ denotes the error function, $\rho(\cdot)$ represents the activation function array and $E(t)$ denotes the new error function.

$$\vartheta(\alpha)=\frac{2\vartheta}{1+|\vartheta|} \tag{10}$$

Where ϑ denotes the soft sign type activation function. Finally, the AIDINN predicted the financial risk. The "artificial intelligence-based optimization" strategy is considered by the AIDINN identifier due to it practically and efficiency. Here, Red Panda Optimization Algorithm (RPOA) is assigned for turning weight parameter of AIDINN.

D. Optimization Using Red Panda Optimization Algorithm (RPOA)

In this segment, the weight parameter $\overline{E}(t), \vartheta(\alpha)$ of AIDINN is optimized using the Red Panda Optimization Algorithm (RPOA) is discussed [29]. A little native animal, the red panda may be found in the eastern Himalaya and southern China. The animal has thick reddish-brown fur on its chest and legs, a mostly white snout, white-lined ears, and a ringed tail. It has black legs and a belly. Its curved, semi-retractile claws and flexible joints make it ideally suited for climbing. Red pandas live in temperate broadleaf, mixed, and coniferous forests. The primary objective of utilizing an optimization algorithm in customer churn prediction is to improve the accuracy of churn prediction models. RPOA tries to achieve this goal by effectively exploring the solution space for optimal or near optimal solutions. Customer churn prediction tasks may need complicated and nonlinear interactions between many elements impacting churn behaviour. RPOA adaptability to complicated data patterns can help capture these subtle correlations and improve prediction accuracy.

1)Stepwise procedure for RPOA

Here, a step-by-step process based on RPOA is outlined to obtain the optimal value of AAIDINN. RPOA first distributes the population evenly in order to maximise parameter AIDINN . Ideal solution promoted using RPOA algorithm, linked flowchart given Figure 2.

Step1: Initialization

Initialize the input parameter, here the input parameter are of AIDINN which is denoted as $\overline{E}(t), \vartheta(\alpha)$.

$$X=\begin{bmatrix} x_{1,1} & x_{1,j} & x_{1,m} \\ x_{i,1} & x_{i,j} & x_{i,m} \\ x_{N,1} & x_{N,j} & x_{N,m} \end{bmatrix} \tag{11}$$

Here X denotes the population of the red panda locations, N denotes the count of red pandas , $x_{i,j}$ represents the ith red panda in jth dimension, and m represents the count of problem variable.

Step2: *Random Generation*

After initialization, weight parameters are formed randomly generated. Best values for fitness are chosen based on a conditional explicit hyperparameter scenario.

Step3: *Fitness Function*

Initialized assessments, random results generated. The function of fitness is increased with values of parameter optimization for weight parameters $\left(\overline{E}(t), \vartheta(\alpha)\right)$ are generator. It's expressed as equation (12).

$$\text{Fitness function} = \text{F} = \text{Optimizing}\left(\overline{E}(t), \vartheta(\alpha)\right) \tag{12}$$

Where $\overline{E}(t)$ represents increasing the accuracy and $\vartheta(\alpha)$ represents decree sing the Error rate.

Step4: *The Strategy of Red Pandas in Foraging* $\overline{E}(t)$

The process of exploration entails looking for uncharted territory in the solution space so that the algorithm might find a variety of solutions. During the exploration phase of RPOA, red pandas' position is modelled based on their natural foraging behaviour. Red pandas use their heightened senses of smell, hearing, and vision to locate food sources and navigate. A new location is allocated to each panda depending on their travelling in the direction of the food source, which is the best choice, in order to simulate the behaviour of red pandas while foraging. The red panda's position is adjusted to the one determined by using equation (14) during the exploration phase if the goal function improves at a new position.

$$PFS_i=\{X_k \mid k\{1,2,\ldots\ldots N\}\ and\ F_k<F_i\}\cup\{X_{best}\} \tag{13}$$

Here PFS_i represents the group of suggested food sources for ith red pand and X_{best} denotes the red panda's location that offers best value for the best candidate solution

$$\overline{E}(t) = x_{i,j} + r \cdot \left(SFS_{i,j} - I \cdot x_{i,j}\right) \tag{14}$$

Where $x_{i,j}$ denotes the ith red panda in jth dimension, r represents the arbitrary value in the range [0, 1], I represents the arbitrarily chosen value from the range {1, 2}, $\overline{E}(t)$ specifies the red panda's new location, $SFS_{i,j}$ denotes the selected food source of the ith red panda in jth dimension .

Step5: Skill in Climbing and Resting on the Tree $\vartheta(\alpha)$

The goal of the exploitation phase is to intensively exploit promising solutions discovered during the exploration phase to further refine and improve them. Red pandas' position in the 2nd stage of the RPOA is determined on their ability to climb and rest on trees. The most of the time, red pandas slumber in trees. Moving towards and climbing the tree causes minor variations in the red pandas' position. To simulate the natural habit of red pandas climbing trees, each panda's position is determined individually. If the goal function becomes better, the novel position replaces the prior position of the red panda is expressed in equation (15)

$$\vartheta(\alpha) = x_{i,j} + \frac{lb_j + r \cdot \left(ub_j - lb_j\right)}{t}, \quad i = 1,2,\ldots,N,\ j = 1,2,\ldots,m\ and\ t = 1,2,\ldots,T \tag{15}$$

Where $x_{i,j}$ denotes the ith red panda in jth dimension, $\vartheta(\alpha)$ indicates the novel position of the red panda based on exploitation phase, lb_j and ub_j denotes the upper and lower bound of the jth dimension, , r represents the arbitrary value inside the range [0, 1], m specifies the count of problem variable, t indicates the algorithm's iteration counter and T represents the maximum count of iteration. In order to improve the algorithm's exploitation and convergence capabilities, RPOA will get the possible solution during the iteration stage. The Flowchart ofRed Panda Optimization Algorithm(RPOA) shown in figure 2.

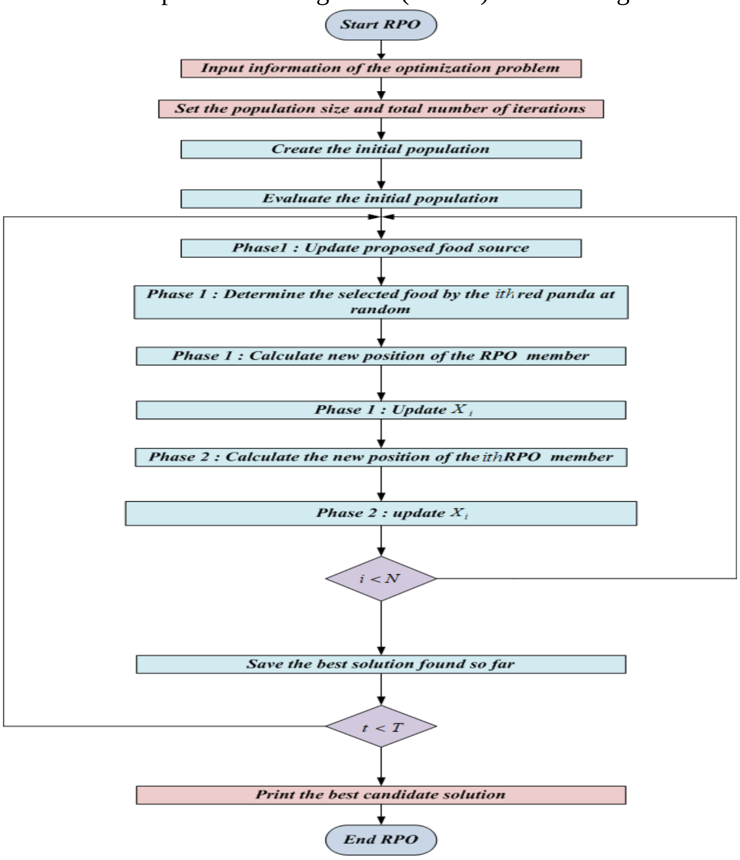

Figure 2: Flow chart of Red Panda Optimization Algorithm (RPOA)

Step6: Termination

In this stage, the weight parameter $\overline{E}(t), \vartheta(\alpha)$ Anti-Interference Dynamic Integral Neural Network are optimized with the help of RPOA, iteratively do again the steps until getting the best solution. Then finally proposed CSN-FREWM-ML-AIDINNpredicted the financial risk in high accuracy.

IV. RESULT WITH DISCUSSION

This section discusses the outcome of the proposed approach. The suggested strategy is then simulated in python using the mentioned performance indicators. The proposed CSN-FREWM-ML-AIDINN approach is implemented in python. Several performance measures like root mean square error, , recall, f1-score, accuracy,error rate, index of error, profitability and development capacity are obtained. The obtained outcome of the proposed CSN-FREWM-ML-AIDINN approach is analysed with existing system like FREWM-LC-BPNN, ECAC-FR-ANN and FREW-WNC-PNN respectively.

A. Performance Measures

When choosing the optimal classifier, this is a crucial step. Performance metrics such as, root mean square error, recall, F1-score, accuracy, error rate, index of error, profitability, and development potential are evaluated in order to gauge performance. To increase the performance metrics' scale, the performance metric is deemed. To increase the performance metrics' scale, the False Positive , True Positive, ,True Negative and False Negative samples are needed.

1) Accuracy

The accuracy of a sample is determined by its proportion of positive and negative samples relative to the total samples. This may be found in equation (16).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{16}$$

Here TP specifies true positive, TN specifies true negative, FN specifies false negative and FP specifies false positive .

2) Recall

True positive rete or sensitivity is terms used to describe recall. It calculates the capability of a classification technique to effectively detect and capture each pertinent instance of a positive class. Thus is expressed in equation (17)

$$\mathrm{Re}call = \frac{TP}{(TP + FN)} \tag{17}$$

3) F1-Score

A machine learning model's performance is assessed using a statistic called the F1-Score. As shown by equation (18), it combines recall and accuracy into a single score.

$$F1 - Score = 2 * \frac{precision * recall}{precision + recall} \tag{18}$$

4) RMSE

The RMSE is a widely used metric for determining the accuracy of a prediction model or estimate. It compute the average magnitude of errors between projected and real values. RMSE is expressed in equation (19)

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \hat{x}_i)^2} \tag{19}$$

Here n specifies the entire count of observations, $\sum$ indicates the sum of overall observation, x_i represents the actual value for observation i , $\hat{x}_i$ represents the expected observation i value , $(\cdot)$ represents the squaring value.

5) Error Rate

The Error rate, also known as the classification error rate, is a metric that measures a classification model's overall accuracy. It denotes the percentage of erroneously classified cases in the dataset and it is given by the equation (20).

$$ErrorRate = \frac{FP + FN}{TP + TN + FP + FN} \tag{20}$$

Here TP denotes true positive, TN specifies true negative, FN denotes false negative and FP specifies false positive.

6) Index of Error

The Index of Error is a metric used to evaluate the accuracy or disparity between predictions or estimates and actual data. It is a frequently utilized metric in domains such as statistics, forecasting, and modeling to assess the efficacy of prediction models or forecasting methodologies. Index of Erroris expressed in equation (21)

$$Index\ of\ Error = \frac{Observed\ value - Forecast\ value}{Observed\ value} \times 100\% \tag{21}$$

7) Profitability

Profitability is an important business indicator that measures a company's capacity to create profit compared to its expenses and sales. There are various methods for calculating profitability; however one frequent calculation is expressed in equation (22)

$$\text{Profitability} = \frac{Net\,\text{Pr}ofit}{\text{Re}venue} \times 100\% \tag{22}$$

Where $Net\,\text{Pr}ofit$ represents the total revenue minus total expenses and $\text{Re}venue$ denoted as the total income generated from sales or operations.

8) Development Capacity

Development capacity is often used to describe a company's or project's ability to grow and expand. Development Capacity is expressed in equation (23)

$$\text{Development Capacity} = \text{Current Capacity} + \text{Potential Capacity} \tag{23}$$

B. Performance Analysis

Fig 3 to 10 illustrates the simulation results of proposed CSN-FREWM-ML-AIDINN method. Then, the proposed CSN-FREWM-ML-AIDINN method is likened with existing FREWM-LC-BPNN, ECAC-FR-ANN and FREW-WNC-PNN methods respectively.

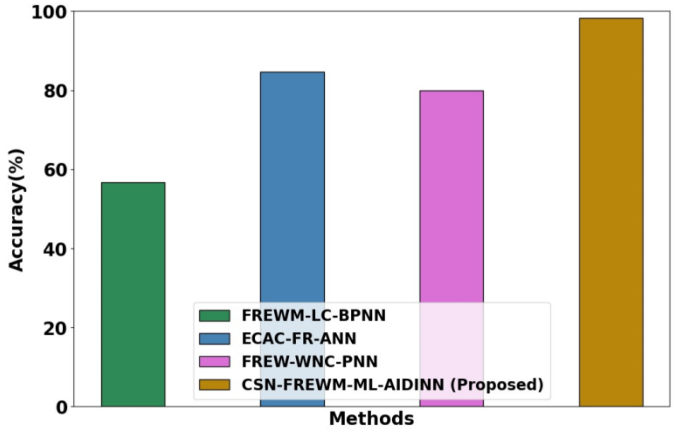

Figure 3: Performance analyses of Accuracy

Figure 3 determines Performance analyses of Accuracy. Accuracy in financial risk prediction is essential for evaluating the success of prediction models. A graph is a concise and easily understandable way to demonstrate the accuracy of various forecasting techniques or algorithms in a setting of financial risk prediction. Each method on the graph indicates the accuracy of a particular model, with longer representing more accuracy and shorter indicating lesser accuracy. Comparing the scale reveals which models outperform others. Furthermore, the placement of methods from left to right depending on accuracy allows for simple comparison between models. Variations and trends in heights could appear, suggesting consistent performance or outliers that warrant additional investigation. Here, the proposed CSN-FREWM-ML-AIDINN method attains 25.65%, 28.40% and 26.48% higher accuracy compared with FREWM-LC-BPNN, ECAC-FR-ANN and FREW-WNC-PNN methods.

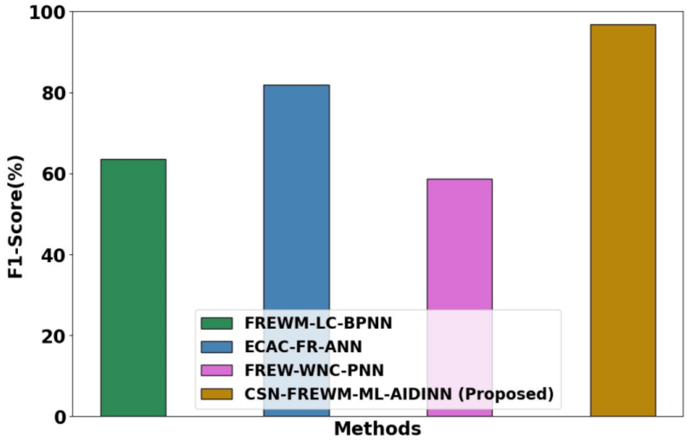

Figure 4: Performance analysis of F1 Score

Figure 4 determines Performance analysis of F1 Score. A graph is a clear and informative perform to display the F1-score of various predictive models or algorithms for financial risk prediction. A comprehensive assessment of a financial risk prediction model's performance is provided by the F1 score, a composite statistic that blends precision and recall. Visualizing the F1 score as a graph provides a clear idea of its effectiveness. The graph typically shows reflecting the F1 score for forecasting risk in finance, respectively. The F1 score balances precision and recall, making it an important indicator for evaluating model performance, particularly when dealing with imbalanced datasets. To interpret the graph, compare the lengths. Greater length means higher F1 scores, which indicate better overall model performance. A balanced F1 score across both categories indicates a robust model capable of correctly predict the risk in finance. Conversely, the F1 scores may highlight areas for improvement, such as fine-tuning feature selection or altering classification criteria. Here, the proposed CSN-FREWM-ML-AIDINN method attains 24.9%, 27.6% and 27.45% higher F1-Score compared with FREWM-LC-BPNN, ECAC-FR-ANN and FREW-WNC-PNN methods.

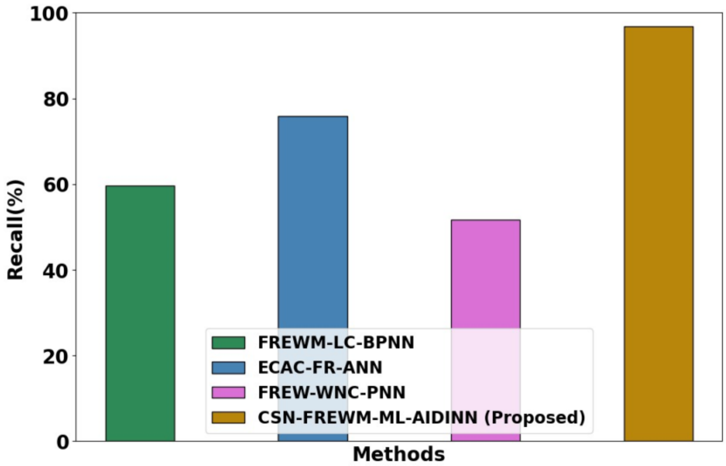

Figure 5: Performance analysis of Recall

Figure 5 determines Performance analysis of Recall. Recall, often referred to as true positive rate is a crucial metric for figuring out whether a “financial risk prediction model”. A graph is a simple representation that depicts the recall of various predictive models. Each method in the graph indicates a specific model's recall, with longer suggesting higher recall and shorter indicating lesser recall. Recall, also referred to as sensitivity, evaluates a model's ability to accurately identify every pertinent occurrence, such as determining which high-risk samples are high-risk among a huge number of high-risk samples. By examining the heights of these methods, one can quickly determine which models excelled at capturing relevant events. Arranging the methods from left to right based on descending recall allows for more efficient comparisons between models. Any notable trends or differences in heights may indicate consistent performers or outliers that require additional research. In conclusion, this visual representation simplifies the comparison process and efficiently communicates the relative recall performance of various models to stakeholders and decision-makers, regardless of technical competence. Here, the proposed CSN-FREWM-ML-AIDINN method attains 25.2%, 24.50% and 19.99% higher recall compared with FREWM-LC-BPNN, ECAC-FR-ANN and FREW-WNC-PNN methods.

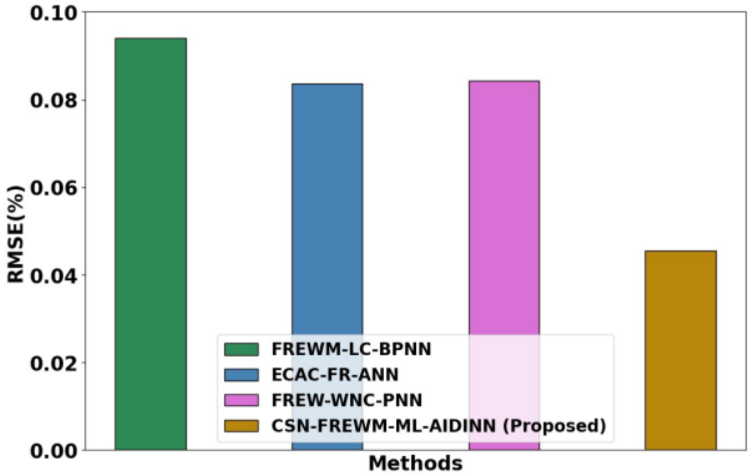

Figure 6: Performance analysis of Root Mean Square Error

Figure 6 determines Performance analysis of Root Mean Square Error.The graph comparing the RMSE of the proposed method to the existing methods in financial risk prediction clearly shows its superiority in obtaining reduced error rates. The graph clearly shows how the HAQP-FBPINN-CLO approach continuously maintains lower RMSE values across different prediction scenarios or timeframes. This error decrease indicates that the method is more accurate and reliable at predicting financial risk characteristics than previous methodologies. Such graphical evidence illustrates the efficiency of the proposed technique in generating more precise forecasts, enabling stakeholders with actionable insights for financial risk management.The RMSE graph clearly shows the proposed method superior performance in financial risk prediction, as it achieves much lower error rates than the existing methods. With clear visual separation, the graph shows how the proposed method consistently maintains tighter clustering around the observed financial risk values, demonstrating improved accuracy and reliability. This substantial reduction in inaccuracy demonstrates the method's effectiveness in delivering more exact projections, allowing stakeholders to make informed decisions about risk control and financial actions. Here, the proposed CSN-FREWM-ML-AIDINN method attains 0.45%, 0.40% and 0.48% lower root mean square error compared with FREWM-LC-BPNN, ECAC-FR-ANN and FREW-WNC-PNN methods.

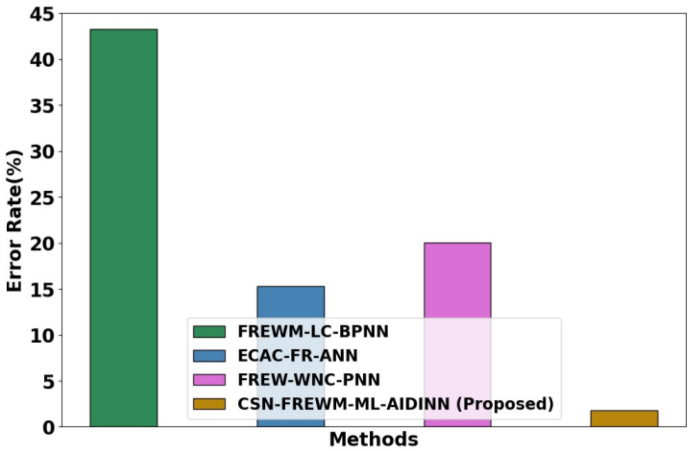

Figure 7: Performance analysis of Error Rate

Figure 7 determines Performance analysis of Error Rate. Error rate, also known as misclassification rate, is an important parameter for evaluating the efficacy of financial risk prediction models. Visualizing error rate as a graph provides a simple representation of model accuracy. The graph typically shows reflecting the error rate for predicting financial risk, respectively. It shows the mistake rate for its respective category. The error rate calculates the proportion of erroneously identified occurrences, revealing the model's overall accuracy. To interpret the graph, compare the methods. It represents lower error rates, implying more model accuracy. A balanced error rate across both categories indicates a model that is accurate in categorizing both churned and non-churned clients. Differences in error rates between the two groups, on the other hand, may reveal opportunities for model improvement. Here, the proposed CSN-FREWM-ML-AIDINN method attains 25.29%,28.36% and 28.55% lower Error rate compared with FREWM-LC-BPNN, ECAC-FR-ANN and FREW-WNC-PNN methods.

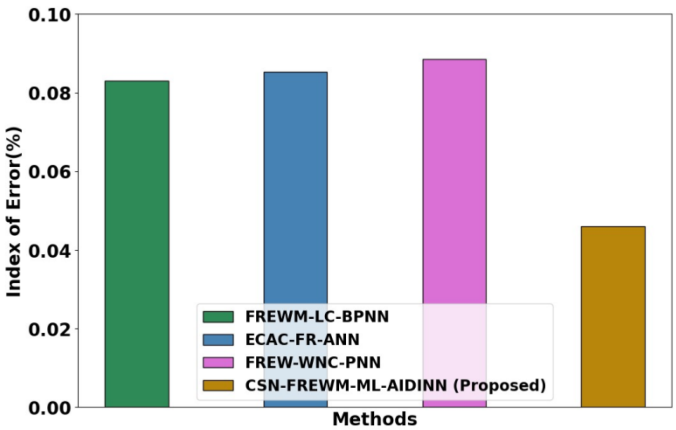

Figure 8: Performance analysis of Index of Error

Figure 8 determines Performance analysis of Index of Error. The Index of Error is a significant indicator in financial risk assessment, providing information about the accuracy and dependability of predictive models. Visualizing this notion as a bar graph can help to explain its relevance without explicitly addressing the variables. In this graph, each bar represents a different model or scenario, with the Index of Error number displayed for each. Each bar's height represents the level of error associated with the model or scenario, with taller bars representing higher error rates. By comparing the heights of the bars, viewers can determine whether models or scenarios have lower error rates and hence are better at anticipating financial hazards. This visual representation emphasizes the necessity of reducing errors in risk assessment in order to make informed decisions and avoid future losses. Here, the proposed CSN-FREWM-ML-AIDINN method attains 0.35%, 0.45% and 0.48% lower Index of Error compared with FREWM-LC-BPNN, ECAC-FR-ANN and FREW-WNC-PNN methods.

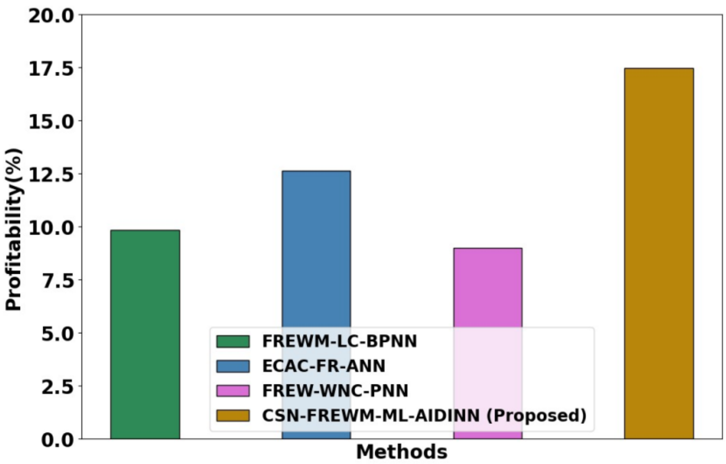

Figure 9:Performance analysis of Profitability

Figure 9 determines Performance analysis of Profitability. The profitability in financial risk using a bar graph provides a clear representation of the performance of various investments or strategies without the need for explicit axis labels. In this graph, each bar represents a distinct investment or risk strategy, and the length of the bars indicates their profitability. It can interpret the graph by comparing the lengths of the bars relative to one another. Wide bars imply greater profitability, whilst simpler bars indicate decreased profitability. This visual representation enables stakeholders to rapidly determine which investments or initiatives are producing the highest returns and which may be under performing. By emphasizing relative variations in bar lengths rather than exact numerical values on swords, the graph emphasizes the overall goal of optimizing profitability in financial risk management. It emphasizes the significance of making educated decisions in order to efficiently allocate resources and maximize profits while reducing potential hazards. Here, the proposed CSN-FREWM-ML-AIDINN method attains 15.29%, 18.36% and 14.55% higher Profitability compared with FREWM-LC-BPNN, ECAC-FR-ANN and FREW-WNC-PNN methods.

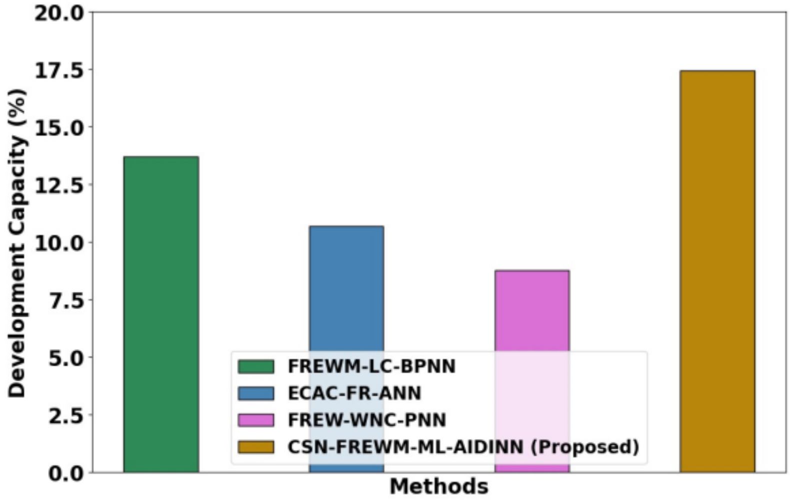

Figure 10: Performance analyses of Development Capacity

Figure 10 determines Performance analyses of Development Capacity. The graph depicts the development capacity for various financial risk levels. It represents different capacity levels, with higher bars signifying more capacity. This graphic provides a clear comparison of development capacity across risk categories, enabling stakeholders to see trends and make educated decisions. This graphical representation is a helpful tool for reviewing resource allocation and prioritizing risk mitigation techniques. The graph displaying Development Capacity in Financial Risk, each bar shows an entity's ability to manage financial hazards, which range from low to high. The height of each bar correlates to the respective capacity level, providing a visual representation of how well-equipped various businesses is to handle financial uncertainties. This graphical representation enables decision-makers to effectively identify areas that require intervention or support, strategize resource allocation, and adjust risk management approaches to unique circumstances. Here, the proposed CSN-FREWM-ML-AIDINN method attains 12.29%, 15.36% and 16.55% higher Development Capacity compared with FREWM-LC-BPNN, ECAC-FR-ANN and FREW-WNC-PNN methods.

C. Discussion

CSN-FREWM-ML is developed in this paper. From the result, it concludes that the proposed method used for the accurate financial risk prediction. Optimizing financial risk prediction with an Anti-Interference Dynamic Integral Neural Network improves accuracy by data normalization. These include the dataset's narrow scope, which may limit the model's capacity to generalize across industries and historical periods. Furthermore, the problem of adequately collecting all relevant risk factors, as well as the interpretability of model results, raises serious concerns about practical implementation. It encourages critical thought on the strengths and flaws of current approaches to financial risk prediction, emphasizing the importance to address these limits and develop the field. The results of the proposed CSN-FREWM-ML methodology are compared to those of current techniques such as FREWM-LC-BPNN, ECAC-FR-ANN and FREW-WNC-PNN.

V. CONCLUSION

In this section CSN-FREWM-ML is successfully implemented. The proposed CSN-FREWM-ML approach is implemented in python. The performance of the proposed CSN-FREWM-ML approach contains 22.36%, 25.42% and 18.17%high accuracy; 21.26%, 15.42% and 19.27% high precision and 25.29%, 28.36% and 28.55% low error rate when analyzed to the existing methods like FREWM-LC-BPNN, ECAC-FR-ANN and FREW-WNC-PNN methods respectively. The proposed research CSN-FREWM-ML addresses the difficulties to use AIDINN to estimate financial risk. This method using an AIDINN for financial risk prediction improves accuracy by data normalization. It highlights the advances made in financial risk prediction while noting its inherent limitations. While the research shows potential, limitations such as dataset scope, risk factor comprehensiveness, and interpretability present substantial obstacles. Nonetheless, it emphasizes the need of continued research in overcoming these challenges and improving the usefulness of financial risk warning models. By addressing these constraints, future efforts can pave the way for more comprehensive and dependable tools for navigating complicated financial landscapes. In future work, the directions could include broadening dataset coverage across industries and time periods, improving risk component inclusion, improving model interpretability, and investigating alternative advanced algorithms such as deep learning to capture complicated financial risk dynamics more accurately. Addressing these shortcomings promises to improve the model's applicability and dependability in real-world decision-making situations.

Acknowledgement

2021 Guangxi Education Science Planning Guangxi Financial Literacy Education Research Project "Financial Literacy Education to Promote rural revitalization Action Research" (2021ZJY879)

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