J. Electrical Systems 20-7s (2024): 3031-3046

Yuechen Zhao[1*]

Construction of Budget Management System Based on Financial Risk Prevention

Abstract: - Optimizing resource allocation to reduce potential hazards is a key component of budget management in financial risk prediction. For the purpose of reducing financial vulnerabilities, it comprises evaluating past data, projecting potential hazards, and strategically allocating cash. Safeguarding against possible losses, effective budget management guarantees that the best risk reduction techniques are in place. In this manuscript, Construction of Budget Management System Based on Financial Risk Prevention (CTN-BMS-FRP) is proposed. Initially input datas are gathered from S&P 500 Companies with Financial Information Dataset. To execute this, input data is pre-processed using Distributed Minimum Error Entropy Kalman Filter (DMEEKF)and it is used to restore the missing data, redundant data, and inconsistent data, from the dataset. Then the pre-processed datas are given to Child Drawing Development Optimization (CDDO)for selecting the features such as sector, prize, symbol, name, Week High, EBITDA, Price/Sales, Week Low, Price/Earnings, Market Cap, Dividend Yield, Earnings/Share, SEC Filings and Price/Book. Then the selected features are fed to Hierarchical Message-Passing Graph Neural Networks (HMGNN)for the prediction of financial risk. In general, HMGNN does not express adapting optimization strategies to determine optimal parameters to ensure accurate financial risk prediction. Hence, the Elk Herd Optimizer (EHO) to optimize HMGNN which accurately predicted the financial risk. Then the proposed CTN-BMS-FRP is implemented in Python and the performance metrics like Accuracy, Precision, Recall F1-Score, and ROC are analysed. Performance of the CTN-BMS-FRP method attains 18.75%, 26.89% and 32.57% higher accuracy; 16.87%, 24.57% and 32.94% higher Precision and 18.43%, 25.64% and 31.40% higher Recall when analysed through existing techniques like discussing the Construction of a Budget Management System Combining Multimedia Technology and Financial Risk Management(BMS-MT-FRM-SVM), Research on Deep Learning-Based Financial Risk Prediction (RSH-FRP-LSTM), Internet Financial Risk Management Under the development of Deep Learning(ITN-FRM-DL) methods respectively.

Keywords: Budget Management, Child Drawing Development Optimization, Distributed Minimum Error Entropy Kalman Filter, Elk Herd Optimizer, Financial Risk, Hierarchical Message-Passing Graph Neural Networks.

I. INTRODUCTION

The effects of the information revolution have permeated every person's daily life since its inception. Through the Internet, it may be accessed from anywhere in the world. It increases exponentially. Massive waste will result if the generated data cannot produce a matching value. It is made possible by the database [1-3]. They must possess greater intelligence in the fiercely competitive world. Data processing is also required in order to forecast future trends in the market. Being content is also essential. They have access to it.These numerous practical requirements have fuelled the development of technology for knowledge discovery in data. Many investigations from various sectors have been conducted in an effort to uncover the wisdom concealed beneath a mountain of data [4-6]. A new field called data mining emerged in response to the demand for real-world uses. Data mining is becoming more and more popular in the current information whirlwind of mobile terminals, cloud computing, e-commerce, and the Internet of Things. Its scope, which has attracted a lot of interest, include bank guarantees, credit evaluation, market research and forecasting, risk detection and assessment, and customer relationship management. In the banking sector, more accurate and tailored marketing can be accomplished by gathering and compiling consumer data and building pertinent data models [7-9]. Simultaneously, data mining technology is employed in the management of financial risks to assess hazardous businesses or financial practices. State that is under control; at the moment, many financial organisations are also actively using data mining techniques in order to predict trends in the market. and evaluate the stock and other financial markets. Additionally, financial monitoring organizations are able to identify potentially hazardous conduct [10-12]. To put it succinctly, data mining will become increasingly relevant across a range of fields as we move into the big data era.As of right now, China is one of the best countries in the world at drawing in international investment. The Chinese government created a wider community of interests and advocated the global economy with your new design. The world economy's integration and diversity have advanced even faster thanks to internet

[1] *Shandong Youth University of Political Science, Jinan, Shandong, 250100, China
[1*]Email: yuechenzhaophd@gmail.com

technology [13-15]. Apart from the seamless commerce resulting from the high degree of economic integration, the risks associated with money that businesses must confront have also grown increasingly varied and unstoppable. The possibility that the company would experience financial losses is found to increase with the number of financial risk sources and directions [16-18].

Financial market analysis is still a complicated topic even with the advent of new tools and algorithms. Its primary goal is to help investors make decisions by examining the changes in the prices of financial goods [19]. Financial risk analysis, a branch of financial market analysis that may be used to predict future trends in the prices of financial commodities, is a hot issue in study these days [20]. Technical analysis and fundamental analysis are the two categories under which traditional financial analysis techniques fall.

The computational cost of the SVM approach limits its effectiveness when working with large datasets. It is also sensitive to parameter selection, necessitating careful tweaking, and it may overfit, particularly in high-dimensional spaces. Though effective in sequence modeling, LSTM approaches have drawbacks. Vanishing gradients can make it difficult for them to capture long-range interdependence. Furthermore, they could be quite resource-intensive to compute and might overfit, particularly in situations with little data. Although very effective, deep learning techniques have drawbacks. A significant quantity of labeled data is frequently needed, which can be expensive or challenging to collect. Moreover, adversarial attacks may compromise the dependability of DL models and cause them to lack interpretability, which makes it difficult to comprehend how they make decisions.

They are able to recognize complex connections between different financial institutions, revealing oblique trends and systemic weaknesses. Through the integration of hierarchical structures, HMGNN improves our comprehension of how risk spreads throughout the financial system at different levels. This gives early notice of possible dangers, enabling proactive risk management. Furthermore, the predictive powers of HMGNN enable portfolio optimization, supporting investors in making well-informed decisions to reduce risk exposure. All things considered, HMGNN is an effective instrument that investors, regulators, and financial institutions may use to negotiate the complexities of the market and protect themselves from unfavorable outcomes.

The main contribution of this study is outlined below.

- In this paper, Construction of Budget Management System Based on Financial Risk Prevention (CTN-BMS-FRP) is proposed.
- S&P 500 Companies with Financial Information Dataset is used to gather the input data.
- After feeding input datas to the CDDO for feature selection, the DMEEKF is used for pre-processing.
- Financial Risk Prediction using Hierarchical Message-Passing Graph Neural Networks (HMGNN).
- Ultimately identifying the input datas accurately with the application of Elk Herd Optimizer (EHO).

Remaining manuscripts arranged as below: Part 2 Literature review; Part 3 Proposed method, Part 4 Result with discussions, Part 5 Conclusion.

II. LITERATURE SURVEY

A number of studies reported in the literature used deep learning based on financial risk prediction; few of them were reviewed here,

Jiang, [21] have presented the BMS-MT-FRM-SVM. The previously stated article investigates and advances the support vector machine model and data mining technique in order to apply feature selection and optimise the model's parameters. In the data mining process, it also develops the data pre-treatment technique. The financial administration of businesses continues to improve thanks to the application of cutting-edge information technology and contemporary management techniques, but there were still many issues. In addition to bolstering financial accounting, businesses should be cognizant of the many threats that corporate financial management may experience from the two-edged sword of financial management informatization. It provides higher accuracy and it provides lower recall.

Huang, and Wei, [22] have presented the RSH-FRP-LSTM. First, the seq2seq model was used to retrieve the financial message's abstract. Different input message lengths were handled by the seq2seq model during the extraction process. Following abstraction, inaccurate data in the financial communications can be successfully filtered, speeding up the next stage of sentiment classification, which was carried out using the model in accordance with the abstracted texts. Financial text-based risk prediction is a significant subset of financial analysis that makes it possible to evaluate the foundations of present financial expectations through computerised analysis of public financial remarks. This study suggests a deep learning method for financial risk prediction based on sentiment categorization. It provides higher recall and it provides lower precision.

Wu, and Zhou, [23] have presented the ITN-FRM-DL. In order to assess the financial risks associated with the Internet, it uses a questionnaire and data analysis, with a particular emphasis on material, moral, technological, social, and psychological concerns. In the area of online financial risk management, research offers theoretical and practical benefits. A number of difficulties have surfaced as Internet finance has grown quickly in terms of both volume and scope. In order to control and reduce the risks associated with Internet finance, deep learning was a potentially useful tool for investigating the best method for analyzing input data.It provides higher F1-score and it provides lower accuracy.

Zhao, et al. [24] have presented the study of performance assessment and big data-driven budget management optimisation for colleges. The integration of big data and thorough budget management was the main topic of the research they were conducting. The paper stated that comprehensive budget management needed to progress beyond its existing condition and that big data technology was required to reach a higher degree of information stage. Because of this, the influence of budget management on scientific research projects in Chinese institutions was investigated in this work using the double subordination fuzzy support vector machine approach. It provides higher F1-score and it provides lower ROC.

Wei, et al. [25] have presented the Problems and Countermeasures of Comprehensive Budget Management in Drilling Enterprises. It focuses on the core elements of a complete budget management model in response to the demands of market-oriented competition, sustainable high-quality development, and real-world development issues in the drilling industry. It provides a succinct analysis of the key issues and notable inconsistencies in drilling firm's present budget management procedures. The focus was on promoting a business-volume-oriented strategy, based on well-established standards and calculating techniques, and implementing a strong and all-encompassing budgeting system from start to finish. It provides higher precision and it provides lower accuracy.

Peng, and H. Huang [26] have presented the Fuzzy Decision making Method based on Cocoso with Critic for Financial Risk Evaluation. Financial risk assessment was crucial for organisations to identify potential financial hazards, provide the foundation for decisions on financial risk management and stop or minimise risk losses. The main issues that come up while thinking about financial risk assessment have to do with severe fuzziness, ambiguity, and inaccuracy. The degrees of membership and non-membership represent the q-rung orthoptic fuzzy set, which was a more effective technique for capturing fuzziness. This article presents a novel fuzzy score function for q-rung orthopairs that can be used to solve comparative problems. It provides higher recall and it provides lower accuracy.

Li, et al. [27] have presented using corporate governance practices to forecast the likelihood of financial hardship. By evaluating the usefulness of various corporate governance components for forecasting financial troubles in a dynamic discrete-time survival analysis model, this work improves the subject of credit risk management. A panel data structure containing a wide range of financial ratios, macroeconomic factors, and corporate governance indices is used throughout the study. It was detailed, current, and comprehensive. The relationship between government ownership and the likelihood of a financial crisis in China was also investigated in this study. The findings imply that while corporate governance by itself was not a reliable indicator of financial hardship, it can enhance the prediction ability of macroeconomic variables and financial measures. It provides higher F1-Score and it provides lower precision.

III. PROPOSED METHODOLOGY

In this section, Construction of Budget Management System Based on Financial Risk Prevention (CTN-BMS-FRP) is proposed. This process consists of five steps: Data Acquisition, Pre-processing, Feature Selection, Prediction and optimization. In the proposed Construction of Budget Management System, Budget datas undergo pre-processing to prepare them for further analysis. Following preprocessing, Financial Information features such as sector, prize, symbol, name, Week High, EBITDA, Price/Sales, Week Low, Price/Earnings, Market Cap, Dividend Yield, Earnings/Share, SEC Filings and Price/Book are selected from each segment. These features are then organized into a feature vector. The final step involves employing a Hierarchical Message-Passing Graph Neural Networks (HMGNN) for financial risk prediction. They facilitate a thorough understanding of systemic risks and well-informed decision-making in financial operations by supporting portfolio diversification, credit risk assessment, fraud detection, and stress testing. The Elk Herd Optimizer

(EHO) method is introduced for the HMGNN. Fig. 1 depicts the block diagram for the proposed CTN-BMS-FRP method. As a result, a thorough explanation of each step is provided below.

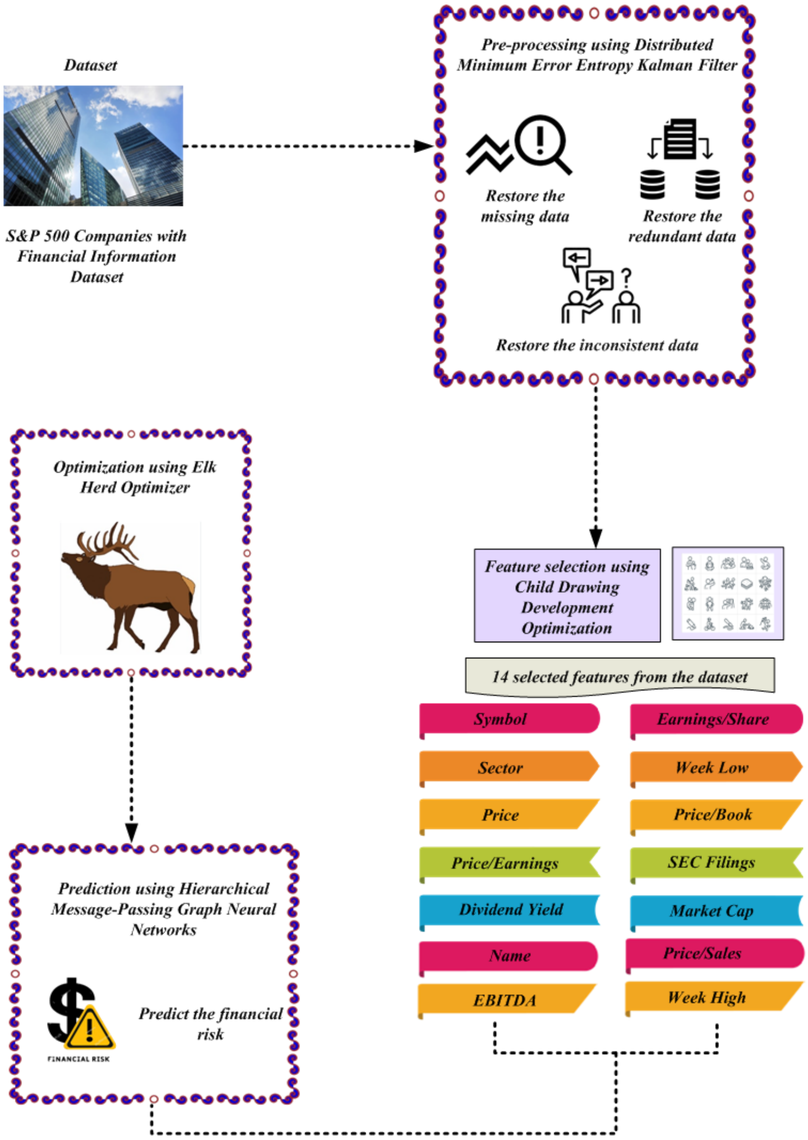

Figure 1: Block Diagram of proposed CTN-BMS-FRP method

A. Data Acquisitions

The input data is gathered from S&P 500 Companies with Financial Information Dataset [28]. A wealth of financial data for S&P 500 index businesses is available in this dataset. The dataset is a useful tool for financial analysis, investment research, and market insights since it includes a variety of basic financial metrics and characteristics. The top 500 publicly traded US equities are included in the free-floating, capitalization-weighted S&P 500 index. A list of all the stocks in the dataset is provided, along with important financial statistics related to them, including price, profits, market capitalization, price to book, price/earnings ratio, and more. Table 1: shows List of features for S&P 500 Companies with Financial Information Dataset

Table 1: List of features for S&P 500 Companies with Financial Information Dataset

SI.NO	Features Names
1.	Sector
2.	Price

3.	Symbol
4.	Name
5.	Week High
6.	EBITDA
7.	Price/Sales
8.	Week Low
9.	Price/Earnings
10.	Market Cap
11.	Dividend Yield
12.	Earnings/Share
13.	SEC Filings
14.	Price/Book

B. Pre-processing Using DMEEKF

In this section, pre-processing using DMEEKF [29] is discussed. In the preprocessing segment, DMEEKF is utilized to restore the missing data, redundant data, and inconsistent data, from the input data. It optimally fuses data from dispersed sensors by decreasing error entropy, which lowers computing load and communication overhead while preserving accuracy and resistance to data attacks. DMEKF improves accuracy by lowering computational and transmission overhead by minimizing error entropy. Effective decision-making and resource allocation in budget management are facilitated by this effective combination of dispersed information. DMEKF protects sensitive financial data by ensuring resistance against data threats. In the end, it makes budget planning, monitoring, and optimization easier in a variety of dynamic settings, which is in line with the main objectives of reaching financial targets and optimizing resource use. Only in the event that the data of its neighbours is not merged can it be simplified to a single node method. The following equation (1) may be used to express the neighbour nodes information fusion.

$$\hat{y}_{i,j} = \hat{y}_{i,j|i-1} + P_{i,j}(x_{i,j} - G_{i,j}\hat{y}_{i,j|i-1}) \tag{1}$$

Where $\hat{y}_{i,j|i-1}$ and $\hat{y}_{i,j}$ are the k^{th} node's a prior on-step prediction and Kalman gain, $P_{i,j}$ is the single node algorithm, $x_{i,j}$ is the local node estimation and $G_{i,j}$ is the diffusion estimation. To obtain diffusion estimation, utilise the nodes' local estimates and the diffusion rule. The diffusion estimation can be expressed in the given equation (2)

$$\hat{y}_j^{Diff} = \sum_{p \in N_p} b_{p,j}\hat{y}_{i,j} \tag{2}$$

Where $\hat{y}_j^{Diff}$ and $\hat{y}_{i,j}$ indicate the fusion node's local estimation and diffusion estimation and $\sum_{p \in N_p} b_{p,j}\hat{y}_{i,j}$ is the information fused in bad communication conditions. The algorithm can be limited to a single-node method alone and not combining the data of its neighbours; otherwise, it is no longer functional. The corresponding fusion can be expressed in the given equation (3)

$$\sum_{p\in N_p} b_{i,j} = T_m,\ b_{i,j} = 0\ \ for\ \ p \notin N_p, \forall p, j, \tag{3}$$

Where $\sum_{p\in N_p} b_{i,j}$ is denotes the time instant, $b_{i,j}$ is the dispersed fusion estimation error's error covariance matrix and T_m is represents the k^{th} node's estimation. At time instant, the ideal single-node Kalman gain. The estimation covariance can be expressed in the given equation (4)

$$Q_{i,j} = (T - P_{i,j}G_{i,j})(F_{j-1}Q_{i,j-1}F_{j-1}^{I} + D_i)(T - P_{i,j}G_{l,i})^T + P_{i,j}R_{i,j}P_{i,j}^T \tag{4}$$

Here, $P_{i,j}G_{i,j}$ represents the node's estimate accuracy, F_{j-1}^{I} indicates the noise in pertinent dimensionalities at a given time instant, D_i is the measurement noise covariance of $R_{i,j}$, and $Q_{i,j}$ is made up of the state noise covariance. The DMEEKF has restored the missing data, redundant data, and inconsistent datafrom the input data in equation (5)

$$b_{i,j} = \frac{1 \big/ Ir(K_{i,j})}{\sum_{p\in N_p} 1 \big/ Ir(K_{i,j})} \tag{5}$$

Where $1 \big/ Ir(K_{i,j})$ can depict how noise in each dimension affects the estimate accuracy characteristics and $\sum_{p\in N_p} 1 \big/ Ir(K_{i,j})$ is represent the estimation accuracy distorted at that moment in time by noise in pertinent dimensionalities. Finally the DMEEKF has restored the missing data, redundant data, and inconsistent datafrom the input data and then the pre-processed datas are given to Child Drawing Development Optimization (CDDO) for selecting the features.

C. Feature selection using Child Drawing Development Optimization (CDDO)

In this section, CDDO [30] is used to select the features from the S&P 500 Companies with Financial Information Dataset. It builds confidence and communication skills by improving self-expression, creativity, and fine motor skills. It also helps with holistic child development and early learning experiences by enhancing problem-solving abilities and offering a nonverbal emotional outlet. It reduces socioeconomic gaps by promoting equitable access to art education. Budget management also fosters cooperation among educators, parents, and community stakeholders, which increases the effectiveness and sustainability of programs. The ultimate goal is to support children's creative potential and holistic development in order to raise a generation that possesses the knowledge and self-assurance needed for success in the future. This technique guarantees thorough development within budgetary constraints by carefully allocating funding for art materials, instructional programs, and instructor training.

Step 1: Initialization

In this period of development, the youngster is learning about hand pressure and movement by watching. Because the youngster is seeing that liner movements produce lines and any other hand motions produce curves, motion can be both linear and curved at arbitrary. Currently, the pressure of the hands is not appropriate; trials in the next stages, accounting for numerous other elements, will help to improve it from being too high or too low later on.The initial population is displayed in equation (6).

$$P = \begin{bmatrix} P_{1,1} & P_{1.2} & P_{1,3} & \cdots & P_{1,d} \\ P_{2,1} & P_{2,2} & P_{2,3} & \cdots & P_{2,d} \\ P_{3,1} & P_{3,2} & P_{3,3} & \cdots & P_{3,d} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ P_{m,1} & P_{m,2} & P_{m,3} & \cdots & P_{m,d} \end{bmatrix} \tag{6}$$

In the case of the indices m and d , j^{th} is the dimension, and bird i^{th} is becomes P .

Step 2: Random Generation

The input parameters are created at arbitrary after setup. The determination of optimal fitness values was dependent on a well-defined hyper parameter situation.

Step 3: Fitness Function

Using the initialised variables, the fitness function generates an arbitrary solution. This is calculated using equation (7).

$$Fitness\,Function = Selected\,Optimal\,Features \tag{7}$$

This is a limited mathematical mechanism with an in-depth explanation of its discovery and application.

Step 4: Exploitation Phase

By manipulating movement and direction, the kid learns to make shapes throughout this stage. The drawings are now more consistent and duplicated, and the child is defining the best sketched drawing thus far and comparing it to the best pattern they have learned. They are also copying the best nearby artists to create new scribbles and comparing them to the group's best sketched drawing thus far. This is calculated using equations (8) and (9).

$$RHP = rand(LB, UP) \tag{8}$$

$$HP = Y(j, r\,and\,(i)) \tag{9}$$

Here, HP denotes the parameter of the current solution that has been chosen, LB represents the current solution's characteristics, and UP represents a factor created to assess the hand pressure of the current solution with a current solution and RHP denotes an arbitrary integer among the problem's lower boundary.

Step 5: Golden ratio

This is the period where the youngster applies the knowledge gained from experiences. He or she makes use of the feedback to notice patterns in the real images, attempt to interpret them, and Practice drawing by copying, refining, and demonstrating your passion.. Another component that is used to modernise the solution and improve its usefulness is the Golden Ratio. A child's drawing's length and width are the two components that make up the solution, and GR is the ratio between the two. This is calculated using equation (10)

$$Y_{j+1} = GR + SR \cdot *(Y_{jlbest} - Y_j) + LR \cdot *(Y_{jgbest} - Y_j) \tag{10}$$

Here, Y_{jlbest} represents the child's finest picture, Y_{jgbest} represents the children's collective best answer, GR is the golden ratio, SR is the skill rate and LR is the level rate.

Step 6: Creativity

In order to make any work of art more visually appealing, creativity is a factor that each child possesses through experience and observation of their surroundings. In order to update the solutions that have a GR or are nearly there, the child is currently combining information; nevertheless, the lack of a pertinent hand pressure in the answer suggests that the child's skills are still growing and that both the golden ratio and the creativity factor need to be used to help.

$$Y_{j+1} = Y_{jMP} + CR \cdot *(Y_{jgbest}) \tag{11}$$

Here, Y_{jgbest} represents the method by selecting one of the top ten children's drawings, Y_{jMP} represents the children's learning pace, CR represents a set value arrived at via trial and error, and Y_{j+1} represents the kid updating the solutions with a GR or one that is almost there by combining information.

Step 7: Termination

In this step CDDO completes, best solution obtained through each process iterations returned as output. Among 14 features CDDO selected 9 features from S&P 500 Companies with Financial Information Dataset and it is represented in table 2.

Table 2 Financial Information Dataset

SI.NO	**Selected Features Names**
1.	Price
2.	Market Cap

3.	Symbol
4.	EBITDA
5.	Week Low
6.	SEC Filings
7.	sector
8.	Dividend Yield
9.	Name

D. Financial Risk Prediction using Hierarchical Message-passing Graph Neural Networks

In this section Financial Risk Prediction using HMGNN [31] is discussed. HMGNN is used to predict the financial risk. In a variety of tasks, including node and graph categorization, they improve interpretability and performance by capturing both local and global structures. Through the capture of complex relationships inside financial networks, it improves forecast accuracy. Second, it makes it possible to represent the hierarchical structures that financial systems naturally have, which produces forecasts that are more reliable. In order to support proactive risk management, the approach seeks to deliver timely risk assessments. It also improves interpretability by illuminating the underlying network dynamics that propel risk. The ultimate objective is to provide relevant insights to stakeholders so they may make educated decisions and successfully mitigate financial vulnerabilities. As an extra step, the hierarchical message-passing mechanism enhances the node representations with multi-grained semantics and long-range interactions. The bottom-up propagation can be expressed in the given equation (12)

$$b_{s_j^t}^{(l)} = \frac{1}{\left|s_j^t\right| + 1}\left(\sum_{s^{t-1} \in s_j^t} g_{s^{t-1}}^{(l)} + g_{s_j^t}^{(l-1)}\right) \quad (12)$$

Here $g_{s_j^t}^{(l-1)}$ indicates the node representation created by the layer, $s^{t-1} \in s_j^t$ is a node, and s_j^t denotes a super node, $\left|s_j^t\right| + 1$ is represented the flat information aggregation and $g_{s^{t-1}}^{(l)}$ is represented the learning process of flat node representation. The objective is to update within-level node representations and compile neighbor information. In the within- level propagation can be expressed in the given equation (13)

$$n_b^{(l)} = AGGREGATE^N\left(\left\{\hat{B}_{uv}^t, b_u^{(l)} \middle| u \in \mathrm{N}^t(v)\right\}\right) \quad (13)$$

Here, $\mathrm{N}^t(v)$ represents a group of nodes that are next to level, $\hat{B}_{uv}^t$ represents the aggregated node representation of v based on local neighbourhood information, and $b_u^{(l)}$ denotes the node representation following bottom-up propagation at the layer. To enable adaptive learning of the contribution weights across different levels through top-down integration. In the top-down propagation can be expressed in the given equation (14)

$$g_v^{(l)} = \mathrm{Re}\,LU\left(X.MEAN\left\{\alpha_{uv} a_v^{(l)}\right\}\right), \forall u \in D(v) \cup \{v\} \quad (14)$$

The collection of different-level super nodes is indicated by $D(v)$, the produced node representation of layer is called $g_v^{(l)}$, the activation function is called $\mathrm{Re}LU$, and α_{uv} denotes a trainable normalised attention coefficient between node to super node. $MEAN$ Indicates an element-wise mean operation. The output representation can be expressed in the given equation (15)

$$Z_V = \sigma\left(\mathrm{X}.\ MEAN\left\{\alpha_{uv} a_v^{(L)}\right\}\right), \ \forall u \in D(v) \cup \{v\} \quad (15)$$

Here, $\mathrm{X}.\ MEAN\left\{\alpha_{uv} a_v^{(L)}\right\}$ provides the final node representation created with each row vector and σ represents the Euclidean normalisation function to reshape data.. Only the supervised environment that was employed in our trials for node categorization is covered here. The HMGNN has predicted the financial risk in equation (16)

$$K = -\sum_{v \in V} x_v^T \log(Soft\max(z_v)) \tag{16}$$

Here, K corresponds for additional task-specific goal functions, $\log(Soft\max(z_v))$ is a representation vector of each node that has been enhanced by multi-grained semantics and illuminating long-range interactions, and x_v^T represents a one-hot vector that indicates the label of the node. Finally the HMGNN has predicted the financial risk. In this work, EHO is employed to optimize the HMGNN optimum parameters $(\sigma\, and\, K)$. Here EHO is employed for turning the weight and bias parameter of HMGNN. For this an optimization algorithm is used which is shown in following section.

E. Optimization using Elk Herd Optimizer (EHO)

In this section the weight parameters $\sigma\ and\ K$ of proposed HMGNN are optimized using the proposed EHO [32] is discussed. The EHO is a metaheuristic algorithm enthused by the herding behavior of elk. It offers several advantages in solving optimization problems.EHO effectively models the behavior of an elk herd to maximize resource allocation, promoting risk reduction and cost-effectiveness. Because of its decentralized design, it is more robust and scalable, making it perfect for unpredictable budgetary conditions. In line with budget management goals, EHO seeks to decrease costs while optimizing returns. Enabling effective financial decision-making and goal accomplishment in a variety of budgetary scenarios, EHO generally simplifies resource allocation procedures.

1) Stepwise Procedure for EHO

Here, the stepwise method is defined for getting the perfect value of HMGNN based on EHO. To optimise the optimal value of the HMGNN, EHO first builds an equally dispersed population.

Step1: Initialization Phase

EHO's initialization approach is comparable to that of other comparative optimization methods. In order to objectively contrast EHO with other algorithms, this is done. Thus, the given equation (17)

$$G = \begin{bmatrix} y_1^1 & y_2^1 & \cdots & y_m^1 \\ y_1^2 & y_2^2 & \cdots & y_m^2 \\ \vdots & \vdots & \cdots & \vdots \\ y_1^{EHS} & y_2^{EHS} & \cdots & y_m^{EHS} \end{bmatrix} \tag{17}$$

Where, G is represent the matrix of size $m \times EHS$; $y^1 < y^2 < y^{EHS}$ is represent the population of the elk solutions

Step2: Random Generation Phase

The generated input parameters after setup at arbitrary. The selection of ideal fitness values was contingent upon an apparent hyper parameter scenario.

Step 3: Fitness Function

The initialised assessments are used to construct an arbitrary solution. It is given by equation (18)

$$Fitnessfunction = Optimization(\sigma\ and\ K) \tag{18}$$

Where σ represent the increase the accuracy and K represent the decrease the computational time.

Step 4: Calving Season σ

The ability of the MH algorithm to explore several search space locations at once is referred to as exploration.. Figure shows how the ten solutions converge. During the first few runs, EHO exhibits the most active exploration. EHO has tremendous potential for scalability and flexibility to complex issues, making it worth exploring further. Thus, the given equation (19)

$$\mathrm{E} = \sigma \min_{i \in (1,2,\ldots,\mathrm{A})} e(y^i) \tag{19}$$

Where, E is represent the create families; A is represent the elks of numbing; $e(y^i)$ is represent the fitness value. Figure 2 shows flow chart of EHO for optimizing HMGNN.

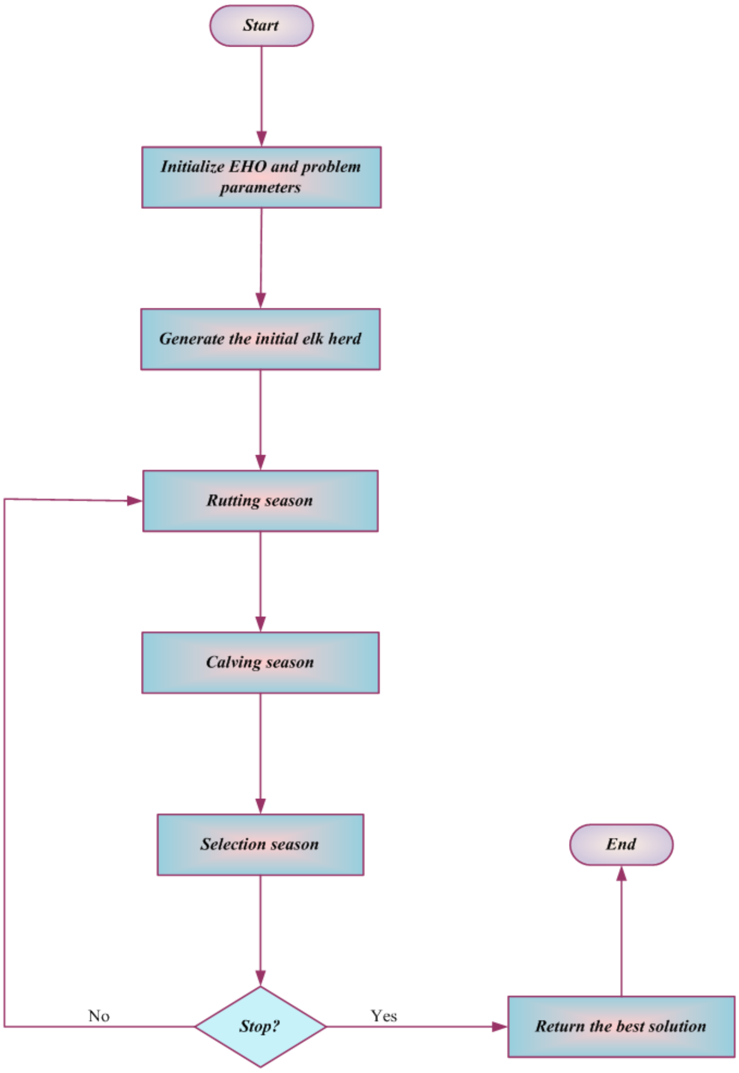

Figure 2: Flowchart of EHO for optimizing HMGNN

Step 5: Selection Season K

The MH algorithm's capacity to travel and locate local optima based on accumulated information is referred to as exploitation. The algorithm's ability to probe farther into promising search sites in order to improve the quality of the result is known as "exploitation.". Thus, the given equation (20)

$$y_j^i(s+2) = y_j^i(K) + \alpha \cdot \left(y_j^l(s) - y_j^i(s)\right) \tag{20}$$

Where, $y_j^i(s+2)$is the j is represent the attribute; i is represent the calf; $s+2$ is represent the iteration.

Step 6: Termination

Using EHO, the weight parameter value of $\sigma\, and\, K$ from HMGNN is optimised. It then repeats step 3 until its halting criterion, $G = G+1$, are satisfied. HMGNN is optimized with EHO.

IV. RESULT AND DISCUSSION

The experimental results of the proposed CTN-BMS-FRP technique have classifying the road damage detection. The proposed technique is executed on the Python. Several performance criteria, including like Accuracy, Precision, Recall, F1-Score, and ROC are evaluated. The results of the proposed CTN-BMS-FRP technique are contrast to those of current techniques like BMS-MT-FRM-SVM [21], RSH-FRP-LSTM [22] and ITN-FRM-DL [23].

A. Performance Metrics

Several performance measures are utilized to run tests and assess system performance. Performance measurements are calculated using the confusion matrix.. Keep a check on performance, including measures like F1-Score, ROC, Accuracy, Precision, and Recall.

1) Accuracy

Equation (21) is used to calculate the accuracy value, which is given as the ratio of the amount of samples properly categorised by scheme to the entire amount of samples.

$$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} \quad (21)$$

2) Precision

It examines a predictive value of the sample, which varies depending on the class for which it is calculated; put another way, it assesses the sample's predictive power, which is ascertained by equation (22).

$$\mathrm{Precision}(P) = \frac{TP}{TP+FP} \quad (22)$$

3) Recall

Sensitivity is a measure that estimates the amount of exact positive forecasts based on the entire amount of positive forecasts. The measurement is determined using equation (23)

$$\mathrm{Recall}(R) = \frac{TP}{(TP+FN)} \quad (23)$$

4) F1 - Score

A composite metric known as the F-score that favours methods with increased sensitivity and challenges for approaches with better specificity and is formulated in equation (24),

$$F1-score = \frac{\mathrm{Precision} * \mathrm{Recall}}{\mathrm{Precision} + \mathrm{Recall}} \quad (24)$$

5) ROC

ROC can be stated as ratio among changes in single variable comparative to equivalent change in another, graphically; rate of change represents slope of line. It is given in equation (25)

$$ROC = 0.5 \times \left(\frac{TP}{TP+FN} + \frac{TN}{TN+TP} \right) \quad (25)$$

B. Performance Analyses

The simulation outputs of CTN-BMS-FRP method are displayed in Figure 3 to 7. The proposed CTN-BMS-FRP approach is compared to existing BMS-MT-FRM-SVM, RSH-FRP-LSTM and ITN-FRM-DL models.

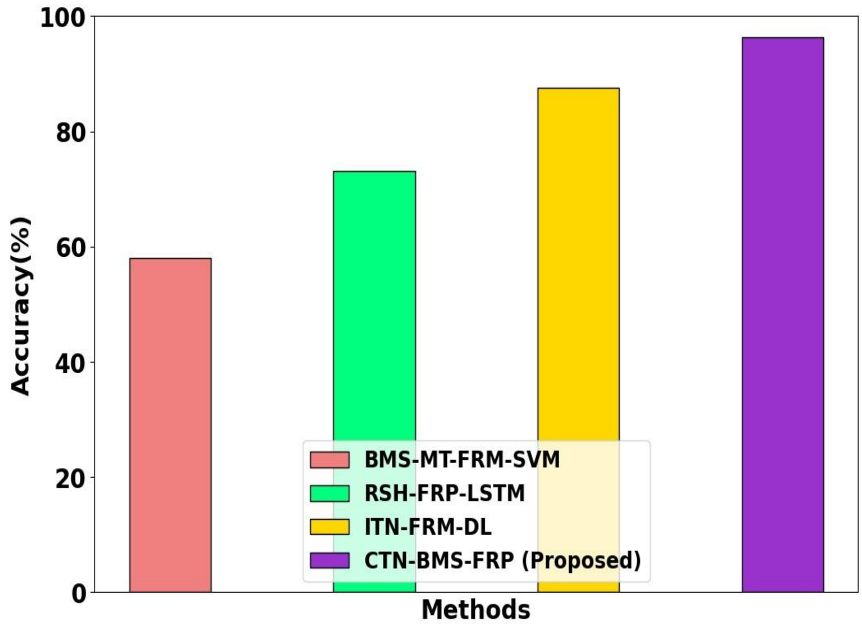

Figure 3: Performance Analyses of Accuracy

Figure 3 shows Accuracy Analyses. The fitness function's assessment value is utilised to determine each person's accuracy rate. Reducing computing complexity, increasing accuracy, and getting rid of superfluous qualities are the objectives. The convolution wrapper method is used to choose the feature subset; the support vector machine algorithm functions as the classifier; the fitness function filters the spring data based on the model's accuracy; and the support vector machine learns from the data. In this context, the proposed CTN-BMS-FRP technique achieves an enhancement of 20.82%, 21.95%, and 22.82% in accuracy as compared to the existing methods as compared to the existing methods BMS-MT-FRM-SVM, RSH-FRP-LSTM and ITN-FRM-DL models respectively.

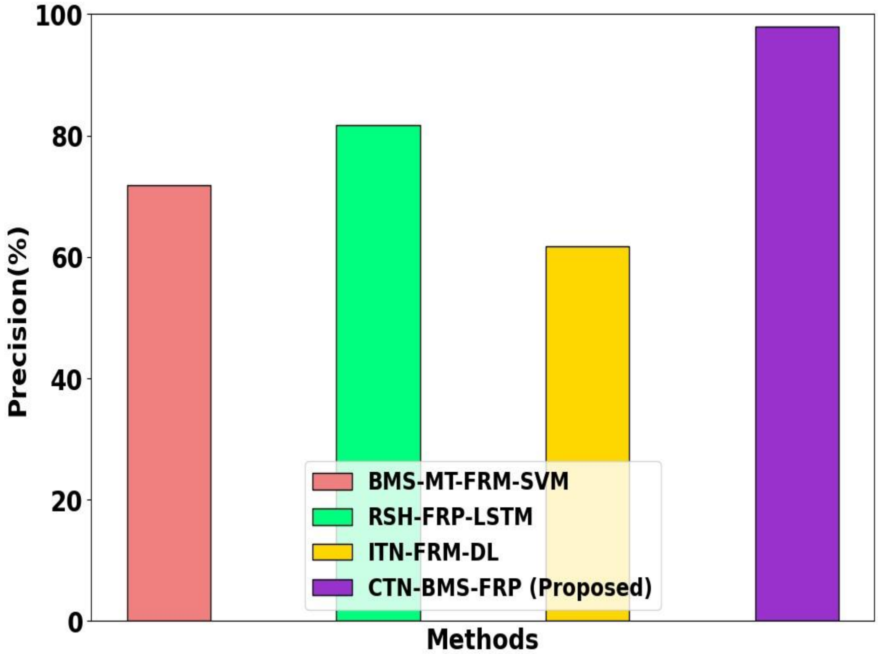

Figure 4: Performance Analysis of Precision

Figure 4 illustrates the Precision analysis. It analyses a sample's predictive value, which varies according on class and can be either positive or negative. They provide information on model reliability by graphically displaying the ratio of real positive predictions to all positive predictions. Stakeholders can evaluate the trade-off between precision and recall by examining each point on the graph, which represents a distinct threshold for risk classification. Greater precision is shown by a steeper upward curve, which also denotes fewer false positives. By assessing the efficacy of risk prediction models and their suitability for reducing financial uncertainties, an understanding of these graphs aids investors and financial analysts in making well-informed judgments. In this context, the proposed CTN-BMS-FRP method achieves increments of 26.70%, 31.24%, and 32.26% in Precision when compared to the existing methods BMS-MT-FRM-SVM, RSH-FRP-LSTM and ITN-FRM-DL models correspondingly.

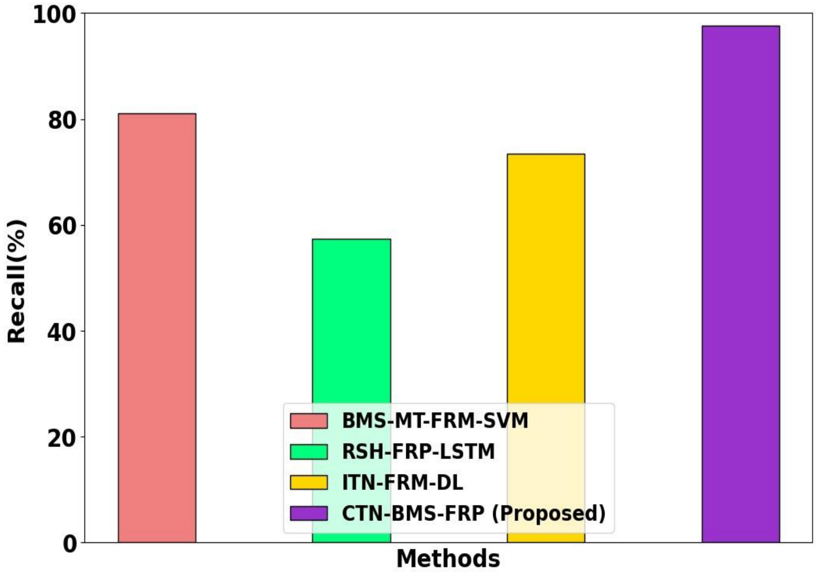

Figure 5: Performance Analyses of Recall

Figure 5 shows recall analysis. A mapping of the relationship between the false negative rate and the true positive rate sensitivity is done across several risk categorization criteria. These graphs provide a thorough understanding of how well the model captures possible dangers by charting recall versus the threshold. A higher recall value reduces the amount of false negatives by showing that the model can identify a greater percentage of real hazards. Recall graphs are used by financial stakeholders to assess how thorough risk detection is, which helps with risk management procedures and strategic decision-making to prevent future financial losses. In this context, the proposed CTN-BMS-FRP techniques accomplishes increases of 21.88%, 20.12% and 23.89% in Recall when compared to the existing methods BMS-MT-FRM-SVM, RSH-FRP-LSTM and ITN-FRM-DL models correspondingly.

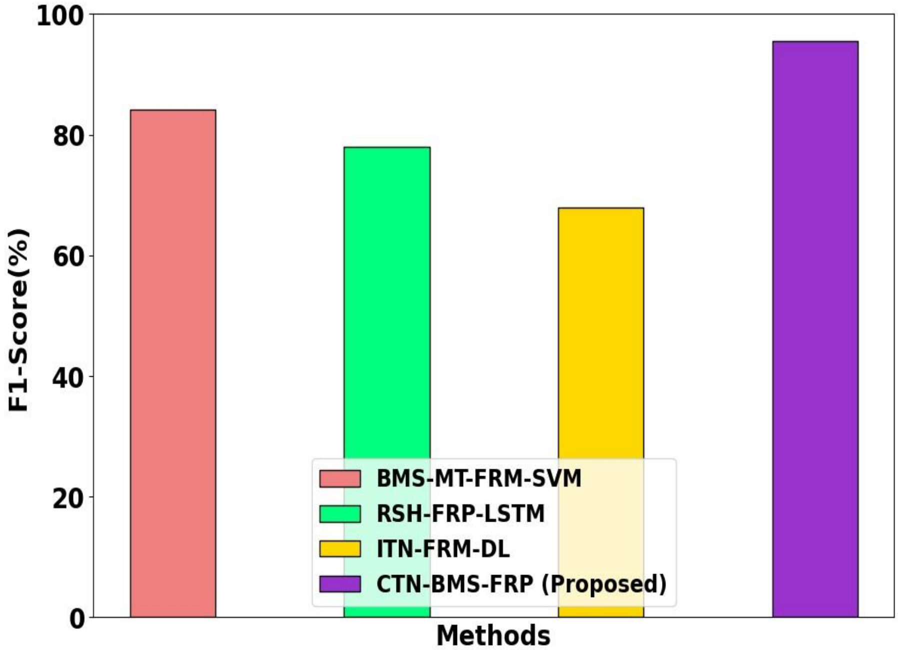

Figure 6: Performance Analyses of F1 score

Figure 6 shows F1-Score analysis. A composite measure called F1-score.A model is more successful at identifying hazards while reducing FP and FN when it has a higher F1-score, which denotes a better balance between precision and recall. Stakeholders can assess the overall predictive power of the model by displaying the F1-score across several thresholds. This helps to guarantee a strong method of reducing financial uncertainty while preserving a respectable degree of precision in risk detection, which helps to optimize risk management tactics. Here, the proposed CTN-BMS-FRPmethod attains 22.44%, 26.45%, and 33.96% higher F1-Score for comparing to the existing BMS-MT-FRM-SVM, RSH-FRP-LSTM and ITN-FRM-DL models correspondingly.

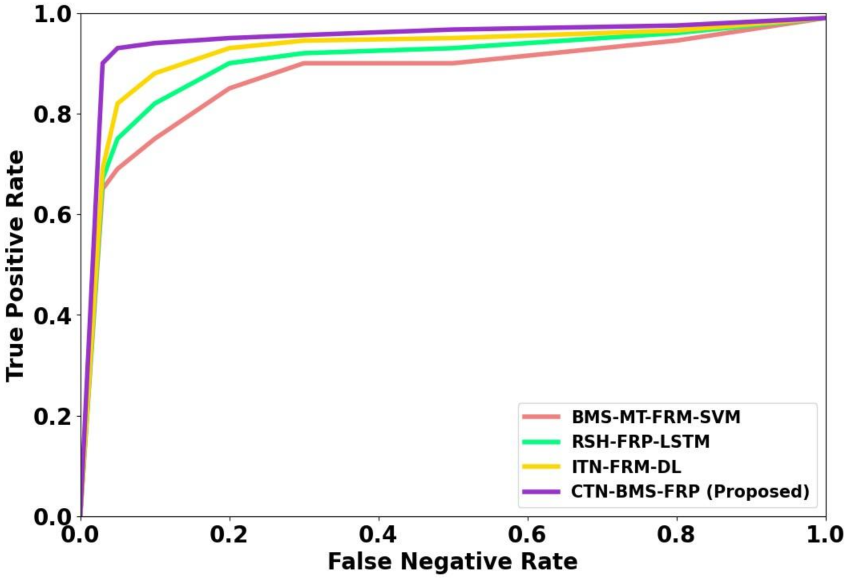

Figure 7: Performance Analyses of ROC

Figure 7 shows ROC analysis. Higher sensitivity and a lower false positive rate are indicators of superior predictive accuracy, as indicated by a steeper ROC curve. Financial stakeholders are able to make well-informed judgments about investment strategies and risk management techniques by using ROC graphs to evaluate the efficacy of risk prediction models. These decisions are based on the model's capacity to accurately identify prospective dangers. These graphs demonstrate the model's capacity to discern between hazardous and non-hazardous assets or events by contrasting the TP rate versus the FP rate. In this context, the proposed CTN-BMS-FRPmethod achieves improvements of 4.66%, 5.22%, and 3.54% in AUC when compared with the existing approaches BMS-MT-FRM-SVM, RSH-FRP-LSTM and ITN-FRM-DL models respectively.

C. Discussion

In summary, new demands for the sound growth of businesses have been raised by the current context of informatization. The advancement of information technology results in Businesses must accelerate the development of financial digitization. In the HMGNN predicted the financial risk and DMEEKF has utilized to restore the missing data, redundant data and inconsistent data from the input data. In the CDDO has selected the features such as mean, entropy, and standard deviation. Numerous performance metrics are assessed, such as F1-Score, ROC, Accuracy, Precision, and Recall. The proposed CTN-BMS-FRP methodology's outcomes are contrasted with those of existing methods like ITN-FRM-DL, RSH-FRP-LSTM, and BMS-MT-FRM-SVM.

V. CONCLUSION

In this section, Construction of Budget Management System Based on Financial Risk Prevention (CTN-BMS-FRP) was successfully implemented. The proposed CTN-BMS-FRP is implemented in python. The proposed technique CTN-BMS-FRP is used to predict the financial risk. Across diverse evaluation metrics, the method consistently showcases substantial enhancements in Accuracy, Precision, Recall, F1-Score, and ROC. As a result, the deep learning prediction models that have been constructed can enable very accurate and dependable prediction of financial risk and restore the missing data, redundant data, and inconsistent data, from the input datas.In comparison to existing methods, the proposed CTN-BMS-FRP methodology achieves 20.82%, 21.95%, and 22.82% high accuracy, 21.88%, 20.12% and 23.89% high precision, 26.70%, 31.24%, and 32.26% high Recall, 22.44%, 26.45%, and 33.96%high F1-Score, and 4.66%, 5.22%, and 3.54% high ROC are compared with existing methods like BMS-MT-FRM-SVM, RSH-FRP-LSTM and ITN-FRM-DL respectively. In the future, the ensemble learning process will improve the performance of the CTN-BMS-FRP approach. The analysis of enterprise financial management's informatization construction not only helps to resolve associated issues and roadblocks but also generates fresh concepts for the advancement and future developments in the fields of financial management innovation and information construction.

REFERENCE

[1] Susan, F., Golrezaei, N. & Schrijvers, O., (2023). Multi-Platform Budget Management in Ad Markets with Non-IC Auctions. arXiv preprint arXiv:2306.07352.

[2] Zweni, A., Yan, B. & Uys, C., (2022). Modelling budget management for public service in South African Municipalities: A structural equation modelling approach.

[3] Savira, A.N. & Wibawani, S., (2024). Transparency of Village Budget Management in Ngaban Village, Tanggulangin Sub-district, Sidoarjo Regency. I*nternationa*l *Journal of Economics Development Research (IJEDR), 5*(1), pp.657-670.

[4] Jia, Q., (2023). Research and Countermeasures on the Comprehensive Budget Management of Oil Field Industry. *Frontiers in Business, Economics and Management, 9*(1), pp.89-93.

[5] Lin, J., Xiao, Y. & Jing, J., (2020, May). Research on University Budget Management under the Background of High-quality Development. *In West Forum on Economy and Management (*Vol. 31, No. 3, pp. 57-64).

[6] Yosefa, A. & Ali, R.M., (2023). Phenomenological Study of Budget Management at the Jambi City Education Office. *Asian Journal of Education and Social Studies, 49*(3), pp.462-474.

[7] Singh, S.N., (2021). Budgetary Management and Control of Finance and Economic Cooperation Organization in Mettu Woreda of Ilu Ababor Zone: An Assessment.

[8] Kamaroellah, R.A. & Syafik, M., (2022). Analysis of Regional Budget Management Performance at Regional Finance Agency of Pamekasan Regency. *The Winners, 23*(2), pp.103-112.

[9] Mulyani, S., Azlimin, A. & Akbar, M.I., (2022). Analysis of the Budget Management and Performance of the Health Center in the Covid-19 Era at the Nambo Health Center, Kendari City. *Miracle Journal of Public Health, 5*(2), pp.155-159.

[10] Sari, W., Disniarti, D., Yushinta, Y., Jawahir, M. & Mutyati, M., (2023). Islamic Education Budget Management in the Time of The Prophet Muhammad SAW. *Innovative: Journal Of Social Science Research, 3*(2), pp.9995-10005.

[11] Gao, J. & You, G., (2024). Exploration of Financial Risk Prevention and Control Mechanisms for Sports and Fitness Clubs in the Big Data Era. *Probe-*Acco*unting, Auditing and Taxation, 6*(1).

[12] Jiang, Q., (2022). Financial Risks and Prevention of Digital Currency. *Frontiers in Economics and Management, 3*(8), pp.507-511.

[13] Li, X., Wang, J. & Yang, C., (2023). Risk prediction in financial management of listed companies based on optimized BP neural network under digital economy. *Neural Computing and Applications*, *35*(3), pp.2045-2058.

[14] Bapat, D., (2020). Antecedents to responsible financial management behavior among young adults: moderating role of financial risk tolerance. *International Journal of Bank Marketing, 38*(5), pp.1177-1194.

[15] Jehi, L., Ji, X., Milinovich, A., Erzurum, S., Rubin, B.P., Gordon, S., Young, J.B. and Kattan, M.W., (2020). Individualizing risk prediction for positive coronavirus disease 2019 testing: results from 11,672 patients. *Chest, 158*(4), pp.1364-1375.

[16] Mahmoudi, E., Kamdar, N., Kim, N., Gonzales, G., Singh, K. & Waljee, A.K., (2020). Use of electronic medical records in development and validation of risk prediction models of hospital readmission:*bmj*, 369.

[17] Ramgopal, S., Ambroggio, L., Lorenz, D., Shah, S.S., Ruddy, R.M. & Florin, T.A., (2022). A prediction model for pediatric radiographic pneumonia. *Pediatrics,* 149(1).

[18] Li, P., Abdel-Aty, M. & Yuan, J., (2020). Real-time crash risk prediction on arterials based on LSTM-CNN. *Accident Analysis & Prevention, 135*, p.105371.

[19] Ghosh, A., Chaudhuri, D., Adhikary, S., Chatterjee, K., Roychowdhury, A., Das, A.K. & Barui, A., (2022). Deep reinforced neural network model for cyto-spectroscopic analysis of epigenetic markers for automated oral cancer risk prediction. *Chemometrics and Intelligent Laboratory Systems, 224*, p.104548.

[20] Wang, H., (2022). Exploration on the organic integration of asset management and budget management in colleges and universities. *International Journal of New Developments in Engineering and Society, 6*(1), pp.51-62.

[21] Jiang, X., (2022). Discussing the Construction of a Budget Management System Combining Multimedia Technology and Financial Risk Management. *Advances in Multimedia, 2022*.

[22] Huang, B. & Wei, J., (2021). Research on deep learning-based financial risk prediction. Scientific programming, 2021, pp.1-8.

[23] Wu, Z. & Zhou, Q., (2023). Internet financial risk management under the development of deep learning. *Pacific International Journal, 6*(1), pp.20-27.

[24] Zhao, W., Li, X. & Zhou, L., Research on performance evaluation and optimization of college budget management under the background of big data. *Applied Mathematics and Nonlinear Sciences*.

[25] Wei, J., (2023). Problems and Countermeasures of Comprehensive Budget Management in Drilling Enterprises. *Advances in Economics and Management Research, 8*(1), pp.220-220.
[26] Peng, X. & Huang, H., (2020). Fuzzy decision making method based on CoCoSo with critic for financial risk evaluation. *Technological and Economic Development of Economy*, *26*(4), pp.695-724.
[27] Li, Z., Crook, J., Andreeva, G. & Tang, Y., (2021). Predicting the risk of financial distress using corporate governance measures. *Pacific-Basin Finance Journal, 68*, p.101334.
[28] https://www.kaggle.com/datasets/franoisgeorgesjulien/s-and-p-500-companies-with-financial-information
[29] Feng, Z., Wang, G., Peng, B., He, J. & Zhang, K., (2023). Distributed minimum error entropy Kalman filter. *Information Fusion, 91*, pp.556-565.
[30] Abdulhameed, S. & Rashid, T.A., (2022). Child drawing development optimization algorithm based on child's cognitive development. *Arabian Journal for Science and Engineering*, *47*(2), pp.1337-1351.
[31] Zhong, Z., Li, C.T. & Pang, J., (2023). Hierarchical message-passing graph neural networks. *Data Mining and Knowledge Discovery, 37*(1), pp.381-408.
[32] Al-Betar, M.A., Awadallah, M.A., Braik, M.S., Makhadmeh, S. & Doush, I.A., (2024). Elk herd optimizer: a novel nature-inspired metaheuristic algorithm. *Artificial Intelligence, 57*(3), p.48.