Management (Montevideo). 2025; 3:178
doi: 10.62486/agma2025178
ISSN: 3046-4048

ORIGINAL

Enhancing Risk Prediction Framework for Corporate Financial Management Using Optimized Neural Network Strategies

Mejora del marco de predicción de riesgos para la gestión financiera corporativa mediante estrategias de redes neuronales optimizadas

Angad Tiwary[1], Mathan N[2], Soumya Mishra[3], Keerthi Jain[4], Yashoda[5], Ameya Ambulkar[6]

[1]Department of Management, ARKA JAIN University. Jamshedpur, Jharkhand, India.
[2]Master Of Business Administration, Sathyabama Institute of Science and Technology. Chennai, India.
[3]Department of Management, Institute of Business and Computer Studies, Siksha 'O' Anusandhan (Deemed to be University). Bhubaneswar, Odisha, India.
[4]School of Business Management, Noida International University. Greater Noida, Uttar Pradesh, India.
[5]Department of Management, Jain (Deemed to be University). Bangalore, Karnataka, India.
[6]ISME, ATLAS SkillTech University. Mumbai, India.

Cite as: Tiwary A, N M, Mishra S, Jain K, Yashoda, Ambulkar A. Enhancing Risk Prediction Framework for Corporate Financial Management Using Optimized Neural Network Strategies. Management (Montevideo). 2025; 3:178. https://doi.org/10.62486/agma2025178

Submitted: 03-03-2024 **Revised:** 02-07-2024 **Accepted:** 14-01-2025 **Published:** 15-01-2025

Editor: Ing. Misael Ron

Corresponding Author: Angad Tiwary

ABSTRACT

Risk prediction is crucial in corporate financial management, influencing strategic decision-making, investment optimization, and proactive mitigation. Traditional models struggle to handle modern financial data's complexity, nonlinearity, and temporal volatility. To address these limitations, this research proposes an advanced, intelligent risk prediction framework based on a Siberian Tiger Optimization-driven Temporal Convolutional Neural Network (STO-TCN). The framework is specifically designed to improve predictive accuracy, adaptability, and robustness in fluctuating financial environments. Research utilizes a comprehensive dataset comprising publicly available corporate financial statements, stock exchange disclosures, and macroeconomic indicators across diverse industry sectors. To enhance data integrity and model performance, two preprocessing techniques were applied: z-score standardization to ensure uniform data scaling and outlier detection to minimize the distortion caused by anomalous data entries. The TCN component effectively captures sequential patterns in financial time-series data, while the STO algorithm optimizes model hyperparameters and network weights, accelerating convergence and reducing overfitting. Experimental results demonstrate that the STO-TCN framework significantly outperforms traditional models with an accuracy of 0,9844, particularly in highly dynamic market scenarios using Python. This predictive framework offers a scalable and adaptive solution for corporate financial risk assessment, with practical applications in investment planning, regulatory compliance, financial governance, and enterprise sustainability. Further investigation incorporates real-time data streams and evaluates performance in small and medium-sized enterprises (SMEs) to broaden its applicability.

Keywords: Temporal Convolutional Neural Network (TCN); Siberian Tiger Optimization (STO); Risk Prediction; Temporal Volatility; Financial Time-Series.

RESUMEN

La predicción de riesgos es fundamental en la gestión financiera corporativa, ya que influye en la toma de decisiones estratégicas, la optimización de las inversiones y la mitigación proactiva. Los modelos tradicionales tienen dificultades para gestionar la complejidad, la no linealidad y la volatilidad temporal de los datos financieros modernos. Para abordar estas limitaciones, esta investigación propone un marco avanzado e inteligente de predicción de riesgos basado en una red neuronal convolucional temporal impulsada por la optimización del tigre siberiano (STO-TCN). El marco está diseñado específicamente para mejorar la precisión predictiva, la adaptabilidad y la solidez en entornos financieros fluctuantes. La investigación utiliza un conjunto de datos completo que comprende estados financieros corporativos disponibles públicamente, divulgaciones bursátiles e indicadores macroeconómicos de diversos sectores industriales. Para mejorar la integridad de los datos y el rendimiento del modelo, se aplicaron dos técnicas de preprocesamiento: la estandarización de la puntuación z para garantizar una escala de datos uniforme y la detección de valores atípicos para minimizar la distorsión causada por entradas de datos anómalas. El componente TCN captura eficazmente los patrones secuenciales en los datos de series temporales financieras, mientras que el algoritmo STO optimiza los hiperparámetros del modelo y los pesos de la red, acelerando la convergencia y reduciendo el sobreajuste. Los resultados experimentales demuestran que el marco STO-TCN supera significativamente a los modelos tradicionales con una precisión de 0,9844, especialmente en escenarios de mercado muy dinámicos utilizando Python. Este marco predictivo ofrece una solución escalable y adaptable para la evaluación del riesgo financiero corporativo, con aplicaciones prácticas en la planificación de inversiones, el cumplimiento normativo, la gobernanza financiera y la sostenibilidad empresarial. Investigaciones adicionales incorporan flujos de datos en tiempo real y evalúan el rendimiento en pequeñas y medianas empresas (pymes) para ampliar su aplicabilidad.

Palabras clave: Red Neuronal Convolucional Temporal (TCN); Optimización del Tigre Siberiano (STO); Predicción de Riesgos; Volatilidad Temporal; Series Temporales Financieras.

INTRODUCTION

The Corporate financial management (CFM) is crucial for an organization's long-term growth, stability, and financial well-being. It involves strategic planning, organizing, directing, and regulating financial activities, like capital investment, budgeting, forecasting, risk assessment, and financial reporting, to optimize shareholder value while preserving financial flexibility.[1,2,3] In a competitive global economy, firms face financial challenges such as market volatility, interest rate fluctuations, currency risks, inflation, credit constraints, and unexpected disasters.[4,5,6,7] Proactive financial management involves anticipating and preparing for potential risks, as reactive solutions are equally important.[2,8,9,10] These risks have the potential to impair long-term growth, threaten business continuity, and undermine corporate performance if not properly anticipated and managed. For CFM, it is therefore imperative to build precise and accurate risk prediction frameworks.[3,11,12] Statistical and rule-based models have been the mainstay of financial risk assessment for many years. When using big, complex, and non-linear financial datasets, these models are typically constrained, despite the fact that they are frequently simple and easy to use.[13,14,15] The hidden links and deeper patterns found in actual financial data could be missed by them.[4,16,17]

The research investigates the link between Corporate Financial Program (CFP) and Corporate Social Responsibility (CSR), focusing on the impact of corporate environmental sustainability (CES) and CSR on CFP.[5] It offers practical suggestions for improving corporate performance and long-term development in Vietnam, but its limited data cloud and novelty of CSR activities may hinder its comprehensive representation. Research examines the impact of ownership structure on the financial performance of 146 manufacturing firms listed on the Pakistan Stock Exchange between 2003 and 2012.[6] It uses agency theory to analyze ownership across government, institutional, insider, and global shareholdings. Tobin's Q, market-to-book ratio, return on equity, and return on assets are used as stand-ins. The research is limited to manufacturing companies and cannot be applied to other industries. Research algorithm investigates the link between corporate financial performance and environmental, social, and governance factors.[7,18,19] It found that environmental, social, and governance (ESG) factors positively affect business profitability, especially for larger companies. However, it also highlighted potential irregularities in ESG evaluation due to adverse environmental scores and firm size bias. The research uses Altman's Z-score and Beneish M-score to evaluate corporate earnings management.[8,20] It reveals a significant correlation between financial distress and earnings manipulation, with companies distorting earnings to maintain competitiveness and credibility. The findings could be beneficial for regulators, policymakers, and state authorities but cannot cover all financial instability or earnings manipulation in different industries.

Research Objective

Using an STO-TCN, this research aims to create an intelligent risk prediction system. The goal is to improve predicting accuracy, adaptability, and resilience in ever-changing corporate finance contexts.

Research Organization

The research was structured in four phases. Phase 1 addresses the introduction and related work, phase 2 presents the methodology, phase 3 explains the result and discussion, and phase 4 provides the conclusion.

METHOD

The proposed approach combines STO with a TCN to enhance risk prediction accuracy and flexibility. It uses Z-score standardization and outlier identification for financial data preprocessing, and dynamically modifies TCN's weights and hyperparameters to maximize performance across significant assessment criteria. Figure 1 presents the overview of the research.

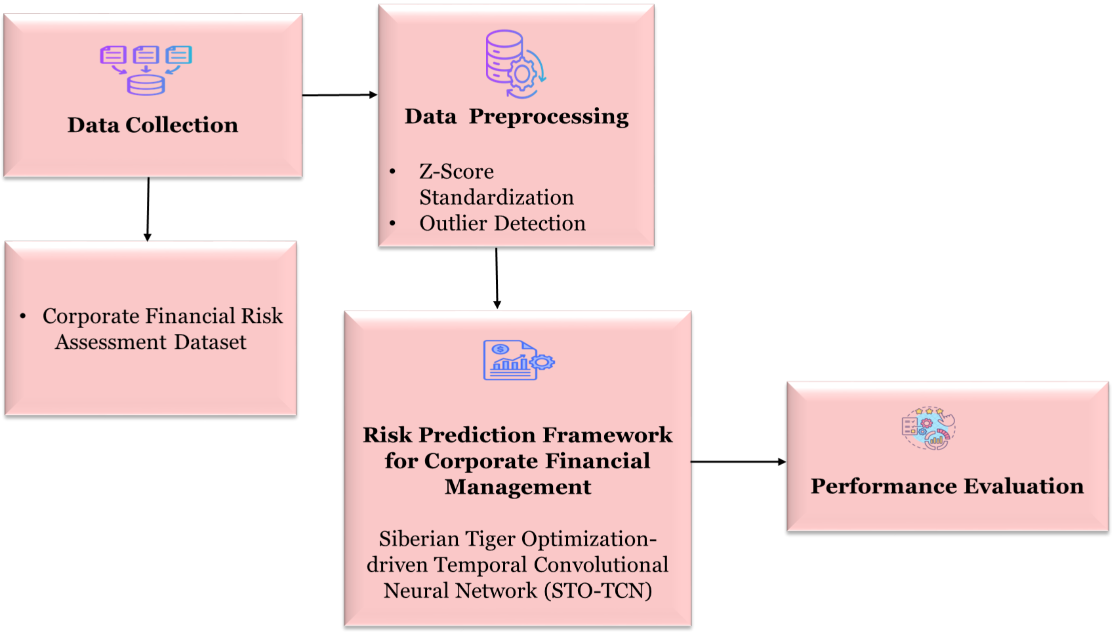

Figure 1. Methodological design

Data collection

Key macroeconomic and financial data from multiple companies in a variety of industry sectors are included in this data collection. The data set was collected from the kaggle score (https://www.kaggle.com/datasets/zoya77/corporate-financial-risk-assessment-dataset). The dataset includes both external economic variables and corporate accounting data, providing a comprehensive overview of a company's financial status. It aims to evaluate and forecast financial risk associated with every business, providing data-driven insights into how external and internal factors impact company viability.

Data Preprocessing

Preprocessing is performed before model training to maintain data quality and consistency, normalizing financial feature scales with Z-score standardization, and using outlier detection methods to remove potential skew points. These performance improvements have made the STO-TCN structure more reliable and efficient.

Z-score standardization

The Z-score normalization is a crucial method, which uses the mean value (μ) and standard deviation value of data to standardize input features, and is crucial for financial risk prediction. Ensuring consistency and comparability across different datasets, like macroeconomic indicators and firm financial statements, is particularly helpful when the minimum and maximum values of financial data are not known or highly changing. P_{nwe} denotes the normalized value, and P is the original data value illustared in equation (1).

$$P_{nwe} = \frac{P-\mu}{\sigma} = \frac{P-Mean(P)}{StdDev(P)} \qquad (1)$$

Outlier detection

Outlier detection is crucial in financial data analysis, particularly for assessing CFM risk. Outliers can reduce model reliability and conclusions due to deviations from norms, data entry errors, or market changes, which can impact the accuracy of the data. By eliminating or managing these anomalies, time-series data pattern

https://doi.org/10.62486/agma2025178 ISSN: 3046-4048

recognition is improved, leading to better financial decisions. Clear and consistent data improves the accuracy and stability of learning techniques and makes it easier to plan investments, decrease risk, and manage finances in dynamic market environments.

Risk Prediction Framework for Corporate Financial Management Using STO-TCN

The hybrid STO-TCN method that has been proposed combines STO for dynamic hyperparameter tuning with TCN for capturing intricate financial time-series patterns. In unstable corporate finance contexts, this synergy improves prediction accuracy, adaptability, and resilience.

Temporal Convolutional Neural Network (TCN)

Stock trends, corporate financial statements, and macroeconomic indicators are examples of sequential financial data that TCN uses as inputs. For $0 < s \leq S$, the input feature vector, denoted by $y_s \in R^{Eq}$, is used at time step s. The financial risk classes are provided by $x_s \in \{1,...,D\}$, which gives the true label. The encoder employs 1D filters for p convolutional layers to understand input sequences' temporal dynamics. The biases vector a^((p)) and the tensor $V^{(p)}$ are parameterized for each layer, with c being the filter time and p ranging from 1,...,p. At time s, the unnormalized activation $F\hat{}_s^{(p)} \in R^{Ep}$ is calculated.

$$\hat{F}_{j,s}^{(p)} = e\,(a_j^{(p)} + \textstyle\sum_{S'=1}^{c} \quad \langle V_{j,s',\cdot}^{(p)}, F_{\cdot,S+C-S'}^{(P-1)} \rangle) \qquad (2)$$

In equation (2), $F^{(p-1)} \in R^{Ep-1 \times Sp-1}$ represents the output activation matrix from the previous layer, containing E_{p-1} feature channels over S_{p-1} time step. The non-linear activation function (·) is a Leaky Rectified Linear Unit (Leaky ReLU), applied element-wise at each time step (s). This formulation supports real-time insights in CFM by allowing the model to derive dynamic risk patterns from previous information. With the time resolution Sp= 1/2 S_{p-1}, 1D Max pooling with width 2 should be used after each layer to shorten the sequence and concentrate on the most prominent temporal patterns presented in equation (3). Channel-wise normalization comes next, where the pooled activation vector $F\hat{}_s^{p}$ is normalized by the largest response at that time step, and n =$F\hat{}_{j,s}^{(p)}$ is utilized with some epsilon ϵ= 1E-5 to avoid decision by zero:

$$F_s^{(p)} = \frac{1}{n+\epsilon} \hat{F}_s^{(p)} \qquad (3)$$

The decoder employs upsampling for frame-level risk prediction in CFM applications, repeating temporal entries using full-length sequences. In equation (4), the output vector $Z\hat{}_s \in [0,1]^d$ evaluates the probability that time step s fits into one of the C financial risk categories, with weight matrix $W \in R^{d \times E0}$ and bias $d \in R^d$.

$$\hat{Z}_s = softmax\big(W\ C_s^{(1)} + d\big) \qquad (4)$$

Several other strategies were investigated, including the use of various convolutional layer layouts, the inclusion of skip connections between layers, and different normalization schemes. The proposed structure performed better overall in capturing the dynamics of financial risk after a thorough empirical test in the context of CFM.

Siberian Tiger Optimization (STO)

An algorithm for bio-inspired metaheuristic optimization called STO simulates the cunning hunting and territorial behaviors of Siberian tigers. STO is a powerful optimization tool for CFM applications, particularly in predicting financial risk. It is used to optimize critical components of a proposed framework, with each ST corresponding to a key model parameter setting. The population of solutions is structured into a matrix, as shown in equation (5).

$$Y = \big[y_{1,1} \ \cdots \ y_{1,n} \ \vdots \ddots \vdots \ y_{m,1} \ \cdots \ y_{m,n}\big]_{m \times n} \qquad (5)$$

To improve risk prediction in CFM, m is the number of potential solutions, and n is the number of parameters being optimized.

For the j[th] solution, the value of the i[th] parameter is shown by each element $y_{j,i}$. Initial places are created within predetermined parameters by using:

$$y_{j,i} = QA_i + \alpha_{j,i}\cdot(VA_i - QA_i) \qquad (6)$$

In equation (6), the ith parameter's lower and upper bounds are indicated by QAi and VAi, respectively, and $\alpha_{j,i}$ is a random number between 0 and 1. The robustness of the optimization process is improved and variety in the search space is ensured by this initialization. The effectiveness of each solution in forecasting financial risk is measured by an objective function, such as enhancing classification accuracy or reducing forecasting error. For every solution, the objective values are saved as in equation (7):

$$P = [P(Z)_1 \ \vdots \ P(Z)_n\,] \qquad (7)$$

In the context of CFM, Pj stands for the jth configuration's performance. There are two main phases to the optimization process. According to their objective values, each tiger chooses a subset of superior solutions during the prey-hunting phase in equation (8):

$$O_j = \{W_q | q \ \in \{1,2, \ldots., \ \ n\} \wedge P_q < P_j\} \cup \{Z_a\} \qquad (8)$$

Where the best-performing option at the moment is Za. Out of this subset, a target solution Sj is selected at random, and the current solution's position changes using:

$$w_{j,i}^{new} = w_{j,i} + \alpha_{ij.}(S_{j,i} - \beta_{j,i}.w_{j,i}) \qquad (9)$$

In equation (9), adaptive control begins the search process by assigning $\beta_{j,i}$ a value of either 1 or 2. The proposed approach integrates the STO algorithm into the risk prediction framework, improving generalization, convergence, and accuracy, promoting financial stability and organizational growth through improved decision-making and proactive risk mitigation techniques. The hybrid STO-TCN framework improves prediction accuracy, convergence speed, and adaptability in volatile financial environments by combining STO for dynamic parameter modification with TCN for temporal financial patterns. This results in a strong, real-time corporate financial risk management system.

RESULTS

The STO-TCN model's implementation (Python 3.10) was tested on corporate financial datasets, revealing complex sequential patterns in financial time-series data. The STO technique dynamically modified the model for improved learning efficiency, offering a scalable solution for real-world financial risk prediction and notable flexibility in changing markets.

Evaluation Metrics

The STO-TCN algorithm for intelligent financial risk prediction was assessed using metrics. The model showed developments in predictive performance, robustness, and computational efficiency in response to data imbalance compared to Backpropagation-aided Neural Network for Optimal Risk Prediction (ORP-BNN)(9) and Synthetic Minority Over-sampling and Edited Nearest Neighbors (SMOTE-ENN) and Natural Gradient Boosting (NGBoost (SMOTE-ENN)).(10)

Prediction rate: table 1 and figure 2 show the prediction rate, which measures the percentage of correct predictions out of the total number of forecasts made by the model, especially in the prediction of financial risk. A higher prediction rate would indicate a more precise recognition of risk patterns, such as investment volatility, market downturn, or credit default, which is crucial for assessing the performance of the STO-TCN algorithm in actual financial situations.

Imbalance detection: imbalance detection in financial risk prediction envolved analyzing the distribution of classes within a dataset. Disparities in imbalance percentages can indicate a distorted dataset, potentially skewing the model towards the majority class and limiting its ability to identify uncommon instances; the results are demonstrated in table 1 and figure 2.

Table 1. Comparison of proposed STO-TCN and existing model

Model	ORP-BNN(9)	STO-TCN (Proposed)
Prediction rate	0,7489	0,8577
Imbalance detection (%)	95,815	97,431
Computing time (min)	10,88	8,70
Model overhead (min)	3,905	2,88

https://doi.org/10.62486/agma2025178 ISSN: 3046-4048

Computing time and Model overhead (Min): the STO-TCN model's training and prediction time are compared in computing time, indicating its effectiveness in changing economic circumstances. Model overhead refers to additional processing time for tasks like hyperparameter tuning and data pretreatment optimization. Implementing data cleaning, STO-TCN, and hyperparameter tuning improves accuracy without undue delay, as shown in table 1 and figure 3.

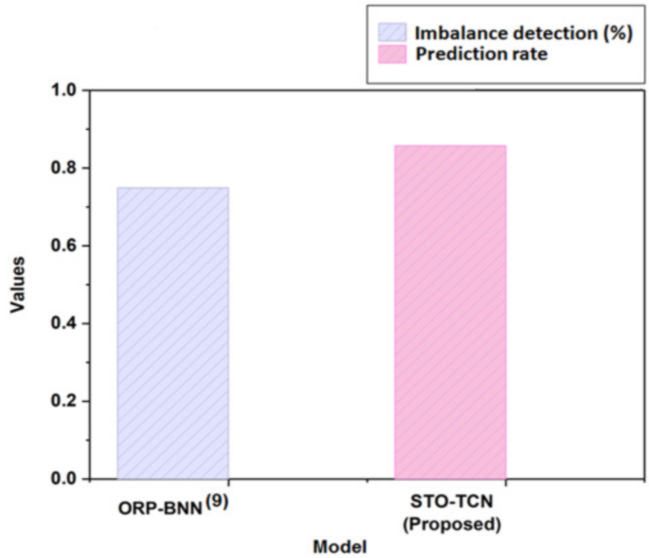

Figure 2. Assessment of Prediction rate and Imbalance detection

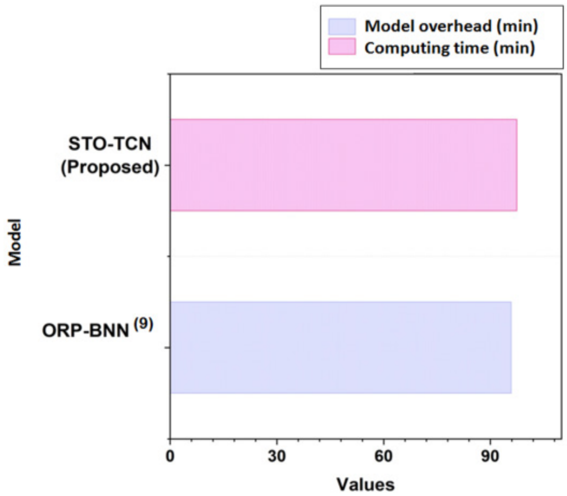

Figure 3. Evaluation of computing time (min) and Model overhead (min)

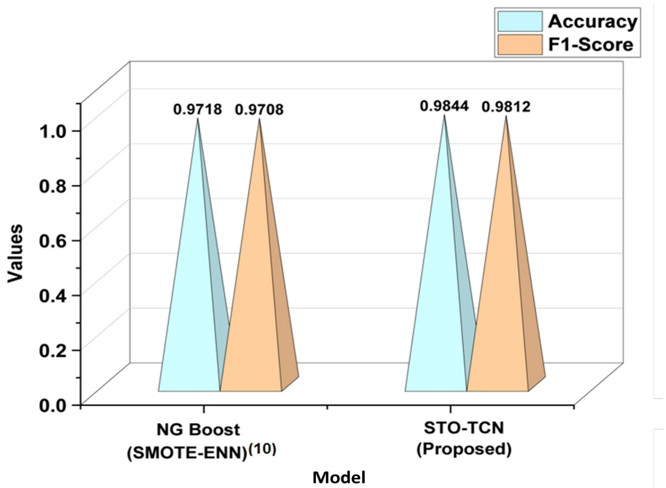

Figure 4. Analysis of accuracy and F1-Score

Accuracy and F1-score: accuracy measures the percentage of true predictions; it shows how reliable the model is overall for determining financial risk levels across a range of scenarios. The F1-score is a balanced evaluation that ensures the model performs well in infrequent instances of high risk. It is a harmonic mean of recall and precisión,as presented in figure 4.

Precision and Recall: precision evaluates how well a model identifies real risks, minimizing false alarms by correctly recognizing real financial hazards without incorrectly labeling stable environments as risky. A key aspect of a model's capacity to accurately forecast positive situations is recall, in which the model records the highest proportion of real risk occurrences and lowers the risk that it would overlook important financial threats, as demonstrated in figure 5.

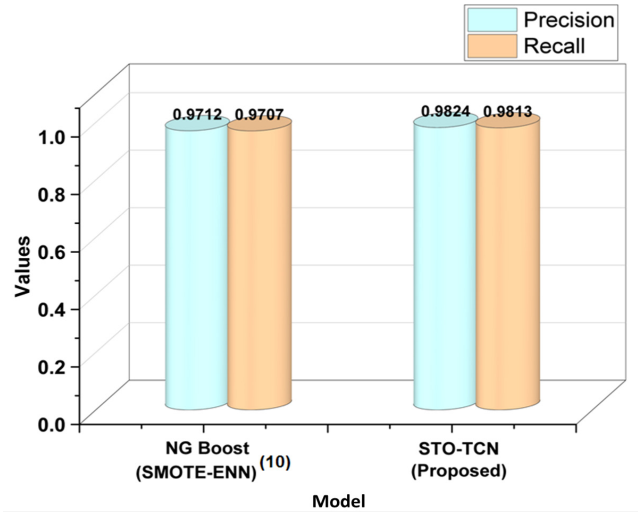

Figure 5. Estimation of precision and recall

DISCUSSION

The ORP-BNN model,[9] despite its potential for dynamic corporate financial environments, has several drawbacks.[21,22] These include potential overfitting, a linear structure that doesn't accurately represent financial system complexity, lack of transparency, and underperformance compared to ensemble methods. NGBoost's black-box nature reduces interpretability and may oversimplify complex financial conditions.[23,24] The SMOTE-ENN and NGBoost-based[10] (Accuracy (0,9718), preicision (0,9712), recall (0,9707), f1-score (0,9708)) financial risk prediction models also have drawbacks, contain risk overfitting, synthetic noise, reliance on historical data, limited generalizability across industries, and exclusion of macroeconomic and qualitative factors. The STO-TCN model uses the TCN component to predict corporate financial risk, capturing temporal and nonlinear data dynamics. It speeds up convergence, reduces overfitting, and improves data quality and model dependability.[25,26]

CONCLUSIONS

Using a STO-TCN, he research suggests a risk forcasting framework for examining the complexity and volatility of modern financial data. The TCN component detects sequential dependencies in financial time-series data, while the STO method dynamically modifies network weights and hyperparameters. A comprehensive dataset of stock market disclosures, macroeconomic variables, and corporate financial statements from several industries was used to assess the system, enabling robust time-series analysis and financial risk forecasting. The proposed STO-TCN algorithm outperforms traditional predictive models, especially in dynamic market conditions, including imbalance detection of 97,431, recall of 0,9813, computing time of 8,70 min, model overhead of 2,88 min, accuracy of 0,9844, prediction rate of 0,8577, precision of 0,9824, and F1-score of 0,9812. The research has limitations due to historical data and financial disclosures, but future expansion utilize real-time data for risk monitoring, SMEs, investment planning, regulatory compliance, and corporate sustainability.

BIBLIOGRAPHIC REFERENCES

1. Ran Z, Gul A, Akbar A, Haider SA, Zeeshan A, Akbar M. Role of gender-based emotional intelligence in corporate financial decision-making. Psychology research and behavior management. 2021 Dec 29:2231-44. https://doi.org/10.2147/PRBM.S335022

2. Chininga E, Alhassan AL, Zeka B. ESG ratings and corporate financial performance in South Africa. Journal of Accounting in Emerging Economies. 2023 Aug 9;14(3):692-713. https://doi.org/10.1108/JAEE-03-2023-0072

3. Mandelman T, Navas C. The future lies in environmental sustainability and technological innovation: Investing in vegan-vegetarian diversity and a robot waiter for a restaurant. eVitroKhem. 2022; 1:6.

4. Juárez GE, Gambino N. Professionalization and Artificial Intelligence in Family Businesses. EthAIca. 2024; 3:139.

5. Estrada Meza RU, Carrillo Regalado S. Impact of the macrobus line on users' origin-destination travel times and costs, Guadalajara metropolitan area, 2012. Transport, Mobility & Society. 2022; 1:10. https://doi.org/10.56294/tms202210

6. Díaz Cruz SA, Batista Villar T, Valido-Valdes D, Núñez Núñez Y, Fernández González JL. Factors that impact in the answer of the ulcers from the diabetic foot to the Heberprot-P®. Podiatry (Buenos Aires). 2025; 4:151.

7. Barclay MJ, Fu F, Smith CW. Seasoned equity offerings and corporate financial management. Journal of Corporate Finance. 2021 Feb 1;66:101700. https://doi.org/10.1016/j.jcorpfin.2020.101700

8. Chen S, Lakkanawanit P, Suttipun M, Xue H. Environmental regulation and corporate performance: The effects of green financial management and top management's environmental awareness. Cogent Business & Management. 2023 Dec 31;10(1):2209973. https://doi.org/10.1080/23311975.2023.2209973

9. Martínez Azcuy G, Otero Martínez A, Marín Álvarez P, Otero Rosales JR, Morejon Carmona L. The bronchial asthma and its association with the changes in the weather. eVitroKhem. 2023; 2:48.

10. Andrés Culetto L, Peña Álvarez E. Open innovation to accelerate the adoption of artificial intelligence in the financial services industry. EthAIca. 2024; 3:138.

11. Estrada Meza RU, Carrillo Regalado S. Social and financial impact of urban mass transportation. Transport, Mobility & Society. 2022; 1:43. https://doi.org/10.56294/tms202243

12. Rodríguez-Portelles AC, Céspedes Rómulo AM. Infrared Thermography as a Diagnostic Tool in Podiatry: Advances, Applications, and Perspectives. Podiatry (Buenos Aires). 2025; 4:156.

13. Tien NH, Anh DB, Ngoc NM. Corporate financial performance due to sustainable development in Vietnam. Corporate social responsibility and environmental management. 2020 Mar;27(2):694-705. https://doi.org/10.1002/csr.1836

14. Din SU, Khan MA, Khan MJ, Khan MY. Ownership structure and corporate financial performance in an emerging market: a dynamic panel data analysis. International Journal of Emerging Markets. 2021 Feb 8;17(8):1973-97. https://doi.org/10.1108/IJOEM-03-2019-0220

15. Federico Gauna H. Proposal for the implementation of a Hygiene, Safety, Environment and CSR plan in the company A.J. & J.A. Redolfi SRL. South Health and Policy. 2022; 1:17.

16. Castro Mejía PJ, Barranzuela Crisant JP, Cisneros Távara MA, Gómez Castillo FF, Manayalle Mera DN, Quintanilla Paico LA, et al. Renewable Energy and the Utilization of Agricultural Waste in Chiclayo. Environmental Research and Ecotoxicity. 2023; 2:53.

17. Angulo Rincón SO, Solarte Solarte CM. Green innovation and territorial development in cocoa-growing communities. Land and Architecture. 2024; 3:107.

18. Paz-Gañan C, González de Paz A, Tang M, Terán López I, Escalona E. Cancer care and its financial impact in Venezuela. A look from critical epidemiology. Nursing Depths Series. 2025; 4:164.

19. Kim S, Li Z. Understanding the impact of ESG practices in corporate finance. Sustainability. 2021 Mar 27;13(7):3746. https://doi.org/10.3390/su13073746

20. Valaskova K, Androniceanu AM, Zvarikova K, Olah J. Bonds Between Earnings Management and Corporate Financial Stability in the Context of the Competitive Ability of Enterprises. Journal of Competitiveness. 2021 Dec 1;13(4):167. https://doi.org/10.7441/joc.2021.04.10

21. Choque Ccanchi CA, Quintana Dragichevich CO, Meneses Claudio BA, Zapana Ruiz JA. Health and safety at work in a financial company in 2023. South Health and Policy. 2023; 2:79.

22. Andrade Rondón GF, Ortiz Vega JA, Murcia Londoño A del P, Ospina Rocha JH. Integral optimization of the Quebrada La Honda water supply system: social and financial impacts in Villavicencio, Meta. Environmental Research and Ecotoxicity. 2024; 3:11.

23. Almirón Cuentas JA, Bernedo-Moreira DH. Ephemeral Architecture as a Solution in the Evolution of Public Spaces. Land and Architecture. 2023; 2:51.

24. Paz-Gañan C, González de Paz A, Villasana P, Escalona E. Financial toxicity of cancer in Latin America and the Caribbean A systematic review. Nursing Depths Series. 2025; 4:167.

25. Gu L. Optimized backpropagation neural network for risk prediction in corporate financial management. Scientific Reports. 2023 Nov 7;13(1):19330. https://doi.org/10.1038/s41598-023-46528-8

26. Zhu Y, Hu Y, Liu Q, Liu H, Ma C, Yin J. A Hybrid Approach for Predicting Corporate Financial Risk: Integrating SMOTE-ENN and NGBoost. IEEE Access. 2023 Oct 10;11:111106-25. https://doi.org/10.1109/ACCESS.2023.3323198

FINANCING
No financing.

CONFLICT OF INTEREST
No conflict of interest.

AUTHORSHIP CONTRIBUTION
Conceptualization: Angad Tiwary, Mathan N, Soumya Mishra, Keerthi Jain, Yashoda, Ameya Ambulkar.
Data curation: Angad Tiwary, Mathan N, Soumya Mishra, Keerthi Jain, Yashoda, Ameya Ambulkar.
Formal analysis: Angad Tiwary, Mathan N, Soumya Mishra, Keerthi Jain, Yashoda, Ameya Ambulkar.
Research: Angad Tiwary, Mathan N, Soumya Mishra, Keerthi Jain, Yashoda, Ameya Ambulkar.
Methodology: Angad Tiwary, Mathan N, Soumya Mishra, Keerthi Jain, Yashoda, Ameya Ambulkar.
Project management: Angad Tiwary, Mathan N, Soumya Mishra, Keerthi Jain, Yashoda, Ameya Ambulkar.
Resources: Angad Tiwary, Mathan N, Soumya Mishra, Keerthi Jain, Yashoda, Ameya Ambulkar.
Software: Angad Tiwary, Mathan N, Soumya Mishra, Keerthi Jain, Yashoda, Ameya Ambulkar.
Supervision: Angad Tiwary, Mathan N, Soumya Mishra, Keerthi Jain, Yashoda, Ameya Ambulkar.
Validation: Angad Tiwary, Mathan N, Soumya Mishra, Keerthi Jain, Yashoda, Ameya Ambulkar.
Display: Angad Tiwary, Mathan N, Soumya Mishra, Keerthi Jain, Yashoda, Ameya Ambulkar.
Drafting - original draft: Angad Tiwary, Mathan N, Soumya Mishra, Keerthi Jain, Yashoda, Ameya Ambulkar.
Writing - proofreading and editing: Angad Tiwary, Mathan N, Soumya Mishra, Keerthi Jain, Yashoda, Ameya Ambulkar.