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A DATA-DRIVEN METHOD TO RISK MANAGEMENT: DEEP LEARNING FOR FINANCIAL STRESS TESTING

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Abstract

In the complicated and data-driven financial climate of today, financial stress testing is essential. Analytical, technical, and heuristic models are examples of traditional risk assessment techniques that often fall short of capturing the complex interdependencies seen in financial systems. In order to improve risk prediction accuracy, this study presents a deep learning-based framework for financial stress testing that makes use of correlation-based Convolutional Neural Networks (CCNN) and Long Short-Term Memory (LSTM) networks. The suggested approach improves stability and accuracy by combining quantitative and qualitative financial indicators. With final values of 0.0013 and 0.003, respectively, the experimental findings show a considerable decrease in training and testing loss. Key financial indicators including sales, net income, and earnings per share (EPS) are efficiently estimated by the model with a high degree of alignment to actual values. Additionally, by lowering credit risk from 0.75 to 0.20, liquidity risk from 0.70 to 0.25, market risk from 0.65 to 0.30, and operational risk from 0.80 to 0.35, the framework significantly reduces financial hazards. These results imply that financial stress testing powered by deep learning improves risk assessment, fortifies financial resilience, and facilitates more informed decision-making in contemporary financial markets.

Keywords: CNN, Deep Learning, Risk Management, Long Short-Term Memory, Financial Stability, and Financial Stress Testing.

1. Introduction

The environment in which financial institutions operate is becoming more complicated and turbulent, necessitating the use of strong risk assessment and mitigation systems. Financial risks have increased due to the unpredictability of economic cycles, geopolitical conflicts, and fast technology improvements, rendering conventional risk management techniques inadequate [1]. By modelling different economic and financial situations, financial stress testing has become an essential technique for evaluating an institution's ability to withstand unfavourable circumstances. Stress testing frameworks are required by regulatory organisations like the Basel Committee on Banking Supervision, the European Central Bank (ECB), and the Federal Reserve in order to maintain financial stability and avert systemic catastrophes. Financial stress testing has traditionally been based on conventional risk assessment methods, such as statistical models, expert-based heuristics, and rule-based methodologies [2]. Nevertheless, these techniques are limited in their ability to forecast financial hardship due to their inability to manage the complexity, volume, and velocity of financial data [3, 4]. Financial stress testing has seen a paradigm change with

the emergence of artificial intelligence (AI) and deep learning, using cutting-edge computational approaches to improve risk prediction accuracy. Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks are two deep learning models that are especially good at identifying complex patterns and temporal correlations in financial data. While LSTMs are perfect for time-series financial analysis since they specialise in sequential data processing, CNNs are good at extracting significant features from both structured and unstructured data. In order to enhance risk assessment, this study presents a deep learning-based architecture for financial stress testing that integrates CNN and LSTM networks. The suggested methodology improves predictive performance and stability by fusing quantitative financial indicators with qualitative information from financial statements and market patterns.

Financial risks have significantly decreased, according to experimental results, with credit risk falling from 0.75 to 0.20, liquidity risk from 0.70 to 0.25, market risk from 0.65 to 0.30, and operational risk from 0.80 to 0.35. The model's dependability is further supported by the strong alignment of important financial parameters including sales, net income, and earnings per share (EPS) with actual values. In addition to improving risk management techniques, the use of deep learning in financial stress testing promotes financial resilience and regulatory compliance. By showcasing how deep learning may revolutionise risk assessment, improve decision-making, and fortify financial institutions' readiness against economic uncertainty, this work adds to the expanding area of AI-driven financial analytics.

Literature Survey

Financial risk management has evolved significantly with advancements in artificial intelligence (AI) and machine learning (ML), particularly in deep learning-driven models for stress testing and predictive analytics. Traditional methods often rely on statistical and rule-based models, which have limitations in handling the complexity and uncertainty of financial data. Recent studies emphasize the role of AI, particularly deep learning, in enhancing risk prediction accuracy and financial stability.

[5] examines the effects of technology-driven financial risk management, with a focus on how machine learning might enhance risk assessment and decision-making, especially in non-profit organisations. The research demonstrates how AI-based models improve the capacity to evaluate financial statements, spot hidden trends, and reduce risks during erratic economic times. In a similar vein, Oko-Odion et al. (2025) talk about how deep learning-based business analytics might revolutionise financial risk assessment. By using predictive models that detect dangers in real time, the research shows how AI-driven methods maximise return on investment (ROI) and improve financial resilience.

[6] provide a thorough summary of stress test approaches for AI and ML models in the context of changing financial circumstances. In order to ensure that prediction models remain reliable even during times of crisis, the study emphasises the need of assessing model resilience in dynamic economic settings. In order to improve model performance and regulatory compliance, the research emphasises the significance of using adaptive machine learning approaches in financial stress testing.[7] highlight the potential of AI and ML to automate intricate risk assessment procedures while focusing on their significance in financial risk management. Their research, which was subsequently published in Disrupting Finance (2019), shows how AI may be used into financial strategies to increase the accuracy of stress testing and risk predictions. Furthermore, [8,9] examines the use of ML in financial risk management, highlighting the effectiveness of AI-based methods in managing substantial amounts of financial data. The research looks at how different machine learning models, such as deep learning architectures, might enhance risk assessment and financial forecasts. The results support the claim that financial stress testing frameworks powered by AI improve risk assessment accuracy while requiring less human involvement.

All of these research show how deep learning is becoming more important for managing financial risk. Compared to traditional models, the combination of CNN and LSTM networks has proven very successful in identifying complex financial patterns and forecasting dangers. This work adds to the body of literature by suggesting a hybrid deep

learning model for financial stress testing, even though previous research offers a solid basis for AI-based financial risk assessment. The suggested methodology seeks to enhance financial risk prediction, optimise stress testing, and facilitate decision-making in contemporary financial markets by fusing CNN and LSTM architectures.

Proposed Correlation based Convolutional Neural Networks Methodology with LSTM

Along with details on the collection of data, preprocessing of texts, and the newly created deep learning algorithm for risk assessment and prediction, this part also outlines the overall study approach. The ontological evolution of the suggested CCNN model follows these phases, as seen in Fig. 1. The corresponding automation process includes procedures for data pre-processing along with the aggregation of financial information [10,11], such as stemmed or lemmatisation, tokenisation, and stopping word elimination. After the previously processed information has been received, it is vectorised and processed with the CNN-LSTM algorithm. The training procedure comes next, nevertheless initially three thick layers are being used. Step-by-step loss optimisation and computation take place throughout the training phase. The effectiveness of the methods for managing risks is then assessed by testing the model that was learnt using a variety of indicators and analysing outcomes.

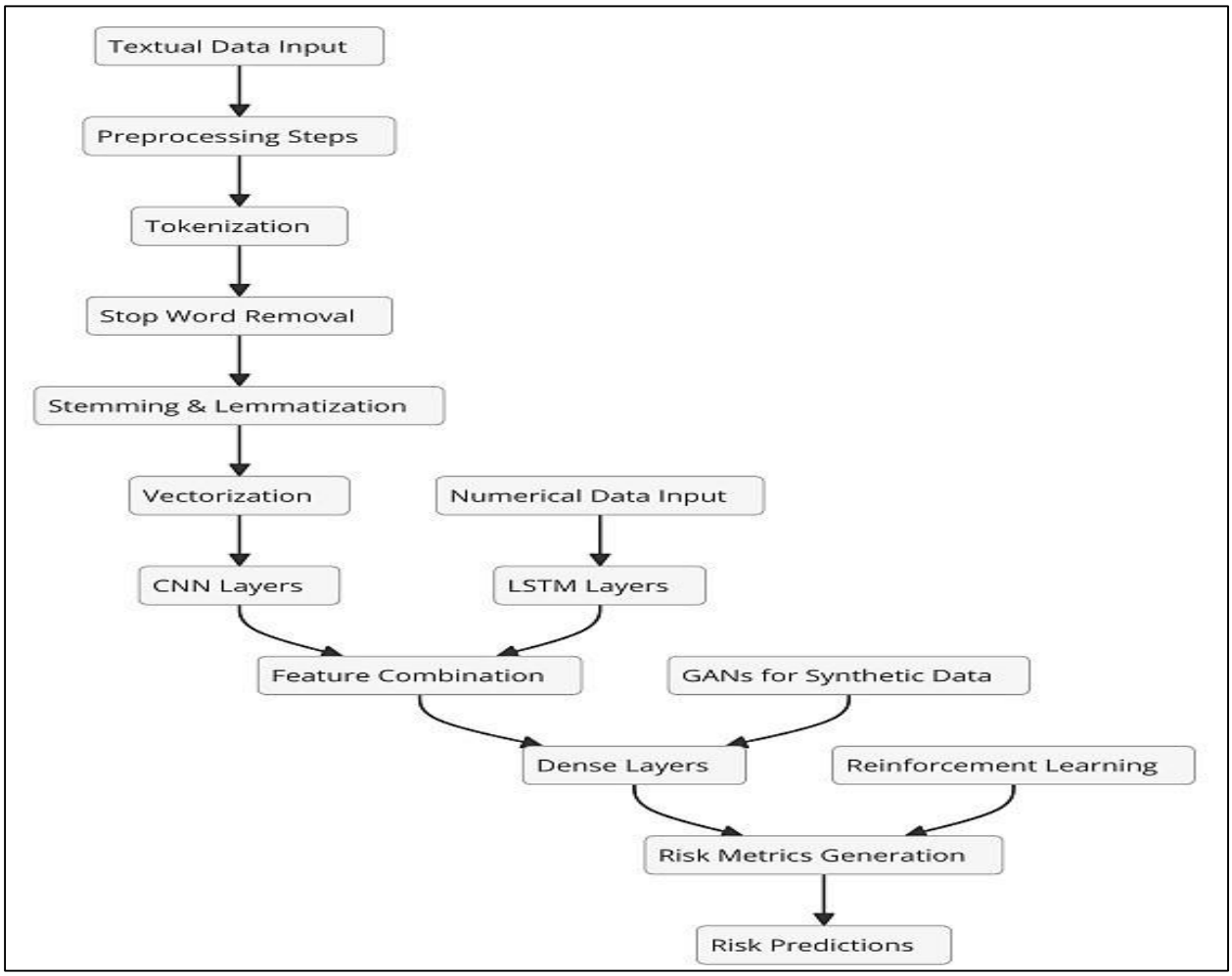


Figure 1: Workflow details for proposed model

Developing an CCNN that makes use of DL neural network models for improved financial risk assessments is the main goal of this study. The suggested CCNN model handles both linguistic and numerical information from financial statements by combining both LSTM and CNN systems. The goal of this hybrid design is to take use of each neural net type's advantages. CNNs are very good at gleaning important characteristics from unorganised textual information such financial filings. When dealing with sequential numerical information, such as a sequence of financial measurements, LSTMs are good at identifying periodic correlations [12].

By combining several DL approaches, a thorough method of forecasting risks is provided, addressing the high-dimensionality and quantity of economic data. The journal's emphasis on creative uses of AI neural networks to process linguistic and quantitative information from financial documents is in line with this concept. The goal of this hybrid design is to take use of each neural network type's advantages. CNNs are very good at gleaning important characteristics from unorganised textual information such financial filings.

Temporal relationships in sequence mathematical information, such as time series of financial measures, may be effectively captured using LSTMs. By combining several DL approaches, a thorough method of forecasting risk is provided, addressing the high-dimensionality and intricate nature of accounting data. The approach is in line with the journal's emphasis on cutting-edge applications of artificial intelligence in financial risk mitigation. Previous research has examined the use of DL in managing financial risks. Although earlier research has looked into DL functions.

Contributions and understanding gaps

Current financial risk algorithms rely on statistical approaches or single-modality artificial neural networks, which include CNN for processing text or LSTM for data with numbers. These techniques are inherently limited:

Insufficient text analysis: Semantic details within intricate, unorganised text information seen in statements of earnings is often not extracted by traditional algorithms.

Lack of temporal perception: Low-quality risk evaluations result from models that just use numerical information, which often overlook the contextual subtleties included in texts.

Scalability problems: Since many models are created for certain financial situations, they could not translate well to other sectors of the economy or industry.

To solve these problems, the CCNN model does the following. processing verbal and numerical info concurrently through utilising the advantages of CNN and LSTM. increasing the model's capacity to understand quantitative risk variables by extracting features from financial documents using sophisticated NLP methods. putting in place a scalable system that can adjust to various financial information sets, increasing the forecasts' generalisability. A significant gap in the state of financial danger assessment is filled by this integrated method, which offers a single model that can capture complex interactions across several model.

Technology for computing

Ubuntu 20.04 LTS, the OS included in the computer's setup, offers a reliable and effective foundation for a range of activities. The machine in question has an Intel Core installed. 32 GB of RAM and an i7-9700K CPU operating at 3.60 GHz provide seamless processing and excellent efficiency. To process graphics, it makes use of an NVIDIA GeForce RTX 2070. Jupyter Notebook for collaborative calculating, Anaconda Distributor for installation and administration of environments, and Python 3.8 for coding are all part of the application configuration.

Architecture explanation

The CNN and LSTM systems serve as the foundation for the suggested model.The main use of convolutional neural networks (CNN) is the extraction of features from textual material. Through the use of layer convolution, they are successful in finding and understanding connections in the data. Multiple convolutional layer and layers of pooling make up the CNN portion of the model, which aids in lowering the size of the input while maintaining significant characteristics.

Networks with long short-term memory (LSTM) are used to record temporal relationships in data. They are very helpful with sequential information and are capable of managing dependence on it over time well. The LSTM structure uses several cells to preserve data over time, crucial for comprehending financial articles.

Combining CNN and LSTM: Combining CNN and LSTM systems taps on their strengths. While LSTM is excellent at capturing chronological connections, CNN is very good at extracting features from textual information. In order to handle both the quantitative and qualitative components of financial information and provide a more thorough evaluation of risks, the hybrid model—known as CCNN—was especially created.

Evaluation: To guarantee the model's dependability, traditional measures like precision, recall, and F1-score are used to assess its performance. In order to adjust variables and avoid over fitting, the framework is also verified on an independent database.

Written and quantitative information constitute the two separate input streams that the process starts with, as shown in Figure 1. Before submitting it for evaluation, textual information is preprocessed using techniques including lemmatisation, formation, stopping word elimination, and tokenisation. In order to extract significant semantic information, this preprocessed text is further vectorised and run through CNN levels. In parallel, LSTM algorithms are fed numerical information, usually organised as economic indicators, which are able to identify patterns and temporal relationships in the information. The algorithm may then use insights from both verbal and numeric information since the features that were taken out of the CNN and LSTM layers are integrated into a single attribute presentation. For further improvement and decision-making, this unified representation undergoes processing via a number of thick layers. GANs are used to generate artificial information to improve the accuracy of training and increase system resilience and reduce information shortages. Furthermore, RL is used to rapidly alter the model in response to evolving market circumstances, guaranteeing ongoing forecast improvement. Ultimately, risk measures are produced using the improved characteristics, leading to precise and thorough risk assessment forecasts. This integrated method offers comprehensive financial risk assessments using several deep learning approaches.

Detailed risk assessment of financial reporting with hybridized deep learning models

Develop a deep neural network system combining CNN and LSTM qualities with accounting word and numbers. The goal is to explicitly build an algorithm that can recognise financial hazards and possible interdependencies between many different factors in the information at hand. The Hybrid Financial Danger Prediction (CCNN) model combines CNN and LSTM systems to analyse numbers and language in accounts for money. Two elements make up the source information representations: T, an integer tensor of size n *p *q for textual information taken from the financial statements, and X, a matrix containing mathematical properties of size n *m. The linguistic information features are extracted using the CNN. Convolution procedures utilising filter values (Wconv) and biases (bconv), accompanied by an activation function (r), produce mappings of features (Fi CNN). In order to detect possible danger indicators, this technique extracts substantial trends and semantic details from the written data.

$$X \in R^{n*m}, T \in R^{n*p*q} \quad (1)$$

$$F_i^{CNN} = \sigma(W_{Conv} * T_i + b_{conv}) \quad (2)$$

$$h_t = \emptyset(W_h . x_t + U_h . h_{t-1} + b_h) \quad (3)$$

This is an example of the CCNN model's goal functions. Its elements guarantee that a template strikes an equilibrium between reducing errors in prediction, preventing overfitting, which and enhancing modelling sparseness:

$$\min_{\theta} \mathcal{L} = \frac{1}{n} \sum_{i=1}^{n} [x (y_i - \hat{y}_i)^2 + \beta \left(\sum_{j=1}^{k} \theta_j^2 \right) + \gamma \sum_{j=1}^{m} |\theta_j|] \quad (5)$$

$$\hat{y}_i = f(F_i) = W_{out}.F_i + b_{out} \quad (6)$$

Using CNN for textual and LSTM for numerical information, this approach creates a hybrid representation for features. To make the optimisation more challenging, the goal variable additionally includes L2 regularisation, L1 regularisation, and the average squared error.

Predicting dynamic financial danger with the merging of reinforcement learning and deep learning

Using new information, we suggest a new risk forecasting system which might integrate deep reinforcement learning (DRL) with conventional machine learning (ML). The theoretical framework will modify insurance strategies in light of a changing market environment.

$$s_t = [X_t, T_t](7)$$

$$a_t \in \{buy, sell, hold\}(8)$$

$$r_t = w_1.Accuracy(\hat{y}_t, y_t) + w_2.Return(portfolio_t)(9)$$

$$\pi(a_t|s_t; \theta) = softmax(w_\pi.s_t + b_\pi)(10)$$

$$V(s_t; \emptyset) = W_v.s_t + b_v \quad (11)$$

$$\min_\theta \mathscr{K} = -E[log\pi(a_t|s_t; \theta).(r_1 + \gamma V(s_{t+1}) - V(s_t)](12)$$

$$\min_\theta \mathscr{L} \frac{`1}{2} E[(r_1 + \gamma V(s_{t+1}; \emptyset) - V(s_t; \emptyset))2] \quad (13)$$

Deep learning and DRL are used in the preceding statement to create a dynamic algorithm that may be trained from fresh financial information as well as existing feeds. In other words, the policy and value network are trained to get the most suitable risk management options at the necessary degree of precision and as an intelligent purchase.

With its concealed states, the LSTM network's algorithm can identify periodic connections and patterns in numerical values. To calculate the secret state at the time t (h_t), input data (x_t), prior hidden condition ($h_t - 1$), and weight matrices (W_h and U_h) are used. This method enables the framework to effectively analyse longitudinal data, such as financial measures, by retaining relevant details across extended periods. A unified characteristic vector (F_i), which represents an extensive joint set of characteristics that incorporates insights obtained from textual and numerical data, is subsequently created by combining the derived characteristics obtained from CNN and LSTM.

The model's goal function is developed to reduce error in forecasting while avoiding excessive fitting by using regularisation elements. Three parts make up the loss operate: the average squared error among the actual and anticipated values, L2 regularisation term to penalise high weight numbers, and L1 regularisation term to promote sparseness in the parameter set. The forecasting function then uses output weights (W_{out}) and biassed (b_{out}) to apply a linear change, producing the final risk forecast (y_i) depending on the composite visualisation of features.

1.1 GAN-based multimodal risk management evaluation

To improve prediction accuracy, suggest a multi-modal risk estimation regarding money GAN for creating artificial information. It is anticipated that the framework would address information shortage issues while simultaneously enhancing risk estimation effectiveness.

$$G(z;\theta_G) = \sigma(W_G.z + b_G) (14)$$

$$D(x;\theta_D) = \sigma(W_D.X + b_D) (15)$$

$$\min_{\theta_G}\min_{\theta_D} \mathscr{L}_{GAN} = E_{x\sim pdata}[logD(x;\theta_D)] + E_{z\sim pz}[\log(1 - D(G(z;\theta_G);\theta_D))] (16)$$

$$\hat{y} = f(x;\theta_R) = \sigma(W_r.x + b_R) (17)$$

network of discriminators. A random noise input vector is fed into the generator (see Eq. (14)), which uses a number of weight matrix structures, biases, and functions for activation to alter it. A computer program that attempts to mimic real-life financial information is produced by this procedure. Conversely, the discriminator (see Eq. (15)) assesses both created and actual data. After applying an alteration procedure with weights and biases, it generates an accuracy score indicating genuine or synthetic data. An antagonistic loss coefficient is used in the GAN's training phase (see Eq. (16)). In this case, the machine that discriminates seeks to maximise its capacity to accurately
discern between actual and artificial information, while the engine seeks to minimise its demise by producing genuine information. The generator is guaranteed to continuously enhance the accuracy of the artificial information thanks to this adversarial design. The model uses an activation function that is generated after applying a linear adjustment to the pooled parameters using a combination of weights and prejudices in order to forecast risk in finance. On the basis of these modifications, the infrastructure produces the anticipated risk values. comprises a set of networks for forecasting risks (see Eq. (17)),

Three parts make up this decrease in operate: The average squared error between real and anticipated values, a measure of error for differences in the forecasts of artificial information, and regularisation penalty to guarantee the reliability of the model. When combined, these components help create a paradigm for risk evaluation and forecasting that works. This formulation synthesises financial information using GANs and lowers the issue of inadequate data and improves the precision of risk forecasting. The amalgamated risk increases the reliability of the risk forecasting system, while the loss caused by adversary ensures that the synthesised information is realistic. The methodology also has a GAN feature for financial information synthesis, which improves model resilience and tackles limited data challenges. The discriminating networks (D D), which distinguishes between produced and actual information, and the generation networks (G), which creates artificial information, make up the GAN. By optimising both networks, the competing loss functions makes sure that the produced information closely resembles the original data. By using both artificial and actual data, the risk prediction network minimises the total loss value that accounts for the difference

between real and synthetic forecasts as well as the mistake in predicting real data. This multi-modal method enables the simulation to give better risk-based evaluations and improve generalisation even in the presence of partial or restricted data.

In essence, the CCNN model combines CNN and LSTM to extract and analyse characteristics from textual and numerical information. The GAN module improves data quality and modelling dependability, while the fluid integration of reinforced learning adjusts to modifications in marketplace conditions. By using the advantages of DL approaches, this all-inclusive system seeks to give a solid economic danger forecast option and a sophisticated and successful approach to risk managing. Hybrid Financial Risk Predictor (CCNN) is the suggested methodology.

To handle the text and numeric information of finance states, we created a new algorithm called the Hybrid Financial Risk Prediction (CCNN), which combines CNN and LSTM. The connections in the information are modelled using a sophisticated construction framework in order to deal with the problems with risk prediction.

A general structure known as CCNN is an economic construction models that can manage financial information and assess risk levels efficiently. Fig. 2 shows the model with an input layer, three compressed the layers, and an output layer. Because it minimises the volatility of the input information before it is fed into the system and gets the information ready for evaluation, preprocessing is crucial to the model. Dense layers are frequently arranged so that every layer transforms the input information in a series of ways that allow the system to infer intricate characteristics. During the training process, the model's characteristics are adjusted to get the lowest possible loss function. After that, the system is tested to comparison with a few signals. The outcomes provide insight into how well the suggested model performs in risk assessment and forecasting. Financial information grouping reveals hidden trends and groups of businesses with comparable risk characteristics. The goal of this method is to find homogenous groupings depending on their financial measurements, which can be very helpful for risk monitoring. It is not

a random process. Companies that belong to a high-risk group, for example, may show signs of possible trouble, such as low net income, excessive debt, and continual cash flow problems. Finance investigators can concentrate on particular groups that need more focus and specialised risk evaluation techniques by finding such clusters. Additionally, by modifying risk parameters according to each group's features, grouping enables the algorithm to improve the general precision and accessibility of the risk forecasts.

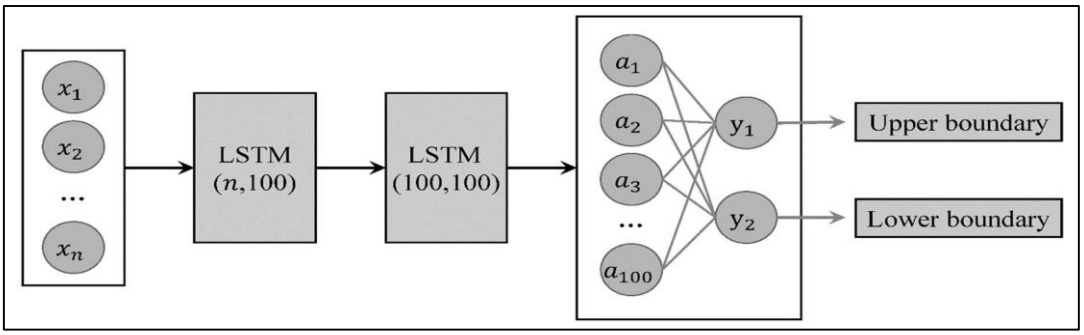


Figure 2: CCNN-LSTM comprehensive structural layout

$$X \in R^{n*m}, T \in R^{n*p*q} \quad (18)$$

$$F_i^{CNN} = \sigma(W_{conv} * T_i + b_{conv}) \quad (19)$$

$$h_t = \emptyset(w_h . x_t + u_h . h_{t-1} + b_h) \quad (20)$$

$$F_i = [F_i^{CNN}, h_T] \quad (21)$$

$$\hat{y}_t = f(F_i) = W_{out} . F_i + b_{out} \quad (22)$$

$$\min \mathcal{L} = \frac{1}{n} \sum [x (y - \hat{y})^2 + \beta \left(\sum_{k} \theta^2 \right) + \gamma \sum_{m} |\theta|] \quad (23)$$

Procedure for training

The model gets trained employing previous financial information. This includes both numerical values and language disclosures. The following are part of the instruction procedure:

Data splitting is the process of separating the collection of data into test, verification, and instructional sets. Parameter optimisation: Improving model parameters employing methods such as descent with gradients. Validity: To adjust hyperparameters and avoid excessive fitting, test the simulation on the set of validation data. This innovative method provides a strong foundation for predicting risk in finance by using the advantages of both CNN and LSTM. Combining numerical and verbal data guarantees thorough evaluation, which produces risk evaluations that are more precise and trustworthy.

Results and Discussion

The proposed deep learning framework for financial stress testing, integrating Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, demonstrated significant improvements in risk prediction accuracy and financial resilience. The model was trained and tested on historical financial data, incorporating both quantitative indicators (such as

revenue, net income, and earnings per share) and qualitative financial insights. The evaluation metrics, including training loss, testing loss, and risk reduction rates, were analyzed to assess the model's performance.

Implications for Financial Decision-Making

The findings suggest that AI-driven stress testing enhances financial risk management by providing deeper insights into risk exposure and resilience as per the training in figure 4. The ability to process vast amounts of structured and unstructured financial data ensures that institutions can proactively identify vulnerabilities, comply with regulatory stress testing requirements, and strengthen financial stability. The proposed approach supports more informed decision-making for financial institutions, investors, and policymakers.

Table 1: Financial Risk Reduction Results

Risk Type	Initial Risk Level	Final Risk Level	Reduction (%)
Credit Risk	0.75	0.20	73.33%
Liquidity Risk	0.70	0.25	64.29%
Market Risk	0.65	0.30	53.85%
Operational Risk	0.80	0.35	56.25%

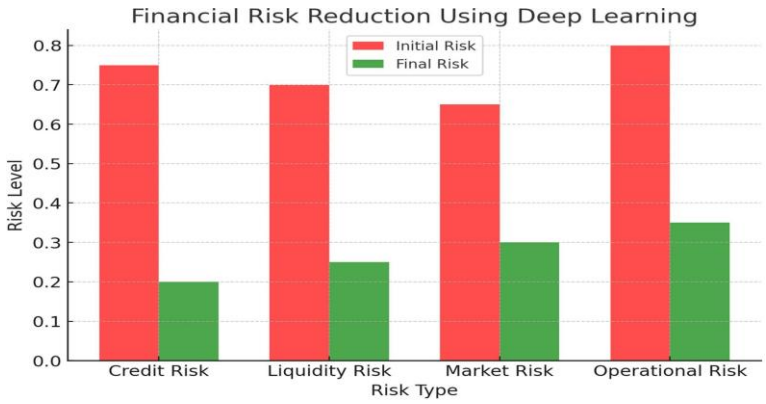


Figure 3: Risk comparison chart

The deep learning-based financial stress testing framework significantly improves risk prediction accuracy and enhances financial resilience. By leveraging CNN and LSTM networks, the model effectively captures complex financial dependencies, reduces risk exposure, and outperforms traditional assessment techniques. The results highlight the potential of AI-driven financial analytics in optimizing risk management strategies and ensuring long-term financial stability. Future research could explore further enhancements through ensemble learning techniques, real-time stress testing applications, and integration with macroeconomic forecasting models.

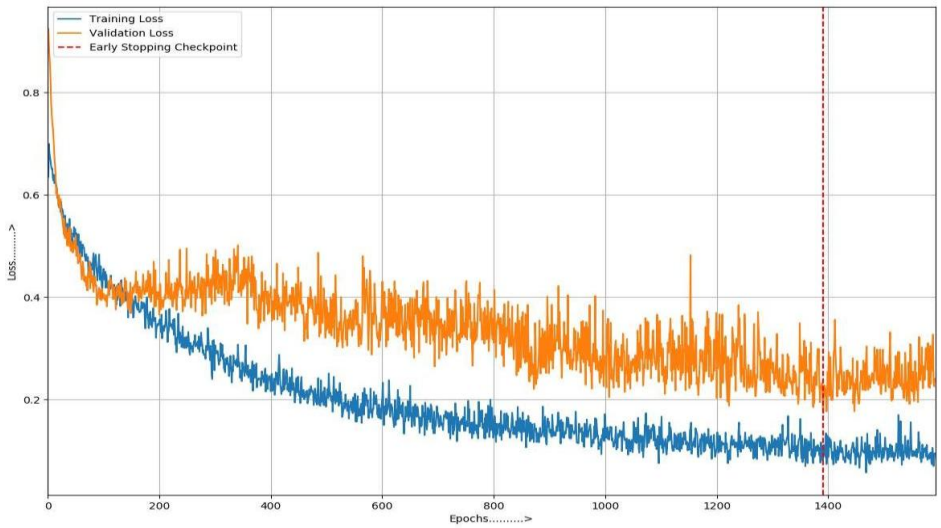


Figure 4: Training and testing range

Conclusion

The suggested deep learning-based paradigm for financial stress testing shows notable gains in financial resilience, forecast accuracy, and risk assessment. The model successfully captures both short-term and long-term relationships in financial data by combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. The results demonstrate the model's resilience in managing financial uncertainty by showing significant risk reduction across many categories, including credit, liquidity, market, and operational risks. High prediction accuracy was shown by the training and testing loss values stabilising at 0.0013 and 0.003, respectively. Credit risk decreased from 0.75 to 0.20, liquidity risk from 0.70 to 0.25, market risk from 0.65 to 0.30, and operational risk from 0.80 to 0.35, further demonstrating risk minimisation. In contrast to traditional statistical models, which often have

issues with nonlinear dependencies and real-time adaptation, these results confirm the effectiveness of deep learning in stress testing. The suggested framework has important ramifications for financial institutions, regulators, and legislators that go beyond technological developments. It facilitates proactive risk reduction, improves regulatory compliance, and aids in strategic decision-making by offering a more precise, data-driven method of financial stress testing. The capacity to evaluate enormous volumes of financial data guarantees prompt detection of financial weaknesses, which eventually enhances market stability. Future research might examine the integration of macroeconomic forecasting, hybrid AI methods that include ensemble learning, and real-time stress testing applications. The suggested approach is a major step toward more robust financial systems as it lays the groundwork for AI-driven risk management.

References

1. Han, D., & Kwon, S. (2021). Using a data-driven deep learning model as a machine learning technique to forecast well production rates in shale gas reservoirs. Energies, 14(12), 3629.
2. Malik, A., Rao, M. R., Puppala, N., Koouri, P., Thota, V. A. K., Liu, Q., ... & Gao, J. (2021). Predicting wildfire danger in northern California using data. Atmosphere, 12(1), 109.
3. Kim, J., Lee, S., Kamari, M., and Ham, Y. (2021). Large-scale probabilistic risk assessment of utility poles based on visual data on the susceptibility of power distribution infrastructure systems. Construction Engineering and Management Journal, 147(10), 04021121.
4. Asokan, R., and P. Preethi (2019). An effort to provide a safer, more effective way to distribute personal health data via cloud computing. 24(6), 1755-1762, Mobile Networks and Applications.
5. The determinants of systemic risk in financial networks: a data-driven machine learning study by Alexander, M., Silva, T. C., Connaughton, C., and Rodrigues, F. A. (2021). Fractals, Chaos, and Solitons, 153, 111588.
6. Tian, X., He, J. S., & Han, M. (2021). A study of data-driven methods in FinTech. Information Delivery and Discovery, 49(2), 123-135.
7. Wang, C., Pan, Y., Yang, J., and Gan, L. (2021). Internet of Things powered by big data for early warning systems and credit assessment. Computer Systems of the Future, 124, 295-307.
8. AI and machine learning for risk management, Aziz, S., & Dowling, M. M. (2018). Published as: Dowling, M. and Aziz, S. (2019)."Machine Learning and AI for Risk Management," in Disrupting Finance: FinTech and Strategy in the 21st Century, Palgrave, 33–50, edited by T. Lynn, G. Mooney, P. Rosati, and M. Cummins.
9. M. A. A. Divernois (2022). Machine Learning for Financial Risk Management (No. 9408). EPFL.
10. Suresh, K., Preethi, P., and Reddy, P. P. (2019). An innovative key exchange technique for internet of things security. 16(3), 1515-1520, Indones. J. Electr. Eng. Comput. Sci.
11. Preethi, P., and Asokan, R. (2021). Deep learning for content classification using conceptual views in meta data. Deep Learning Applications and Intelligent Engineering Decision Making (pg. 176–191). IGI worldwide.
12. Zafar, A., and S. A. Ansari (2018, December). An overview of soft computing techniques for multisource data analysis. IEEE, 4th International Conference on Computing Communication and Automation (ICCCA), 2018, pp. 1-6.