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VISUALIZING DYNAMIC BALANCE-SHEET RISK IN NON-BANKING FINANCIAL COMPANIES THROUGH AI-ENABLED CASH-FLOW NETWORKS

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ABSTRACT

Non-Banking Financial Companies (NBFCs) play a crucial role in the Indian credit landscape. However, their inherent vulnerabilities to liquidity crises position them as highly susceptible to significant shocks. Current approaches to risk assessment for these companies are inadequate for understanding the dynamics of liquidity risk. An AI-enabled approach to modeling the dynamic balance sheets of NBFCs using high-frequency data on their cash flows can help improve risk assessment for these companies. A network of NBFCs can be represented as a graph, with each NBFC as a node in the graph and the transactions between these companies forming the edges of the graph. The AI model that can be used to analyze this graph is a Temporal Graph Neural Network (TGNN). TGNNs are deep learning models specifically designed to learn from network graphs and capture the relationships between the entities represented in the graph nodes. On top of the TGNN, a dynamic risk index for NBFCs can be created by calculating various metrics for the graph created by the NBFCs. These metrics will represent the various aspects of the risk for these companies at any given time. Furthermore, the model can be evaluated using high-frequency datasets of NBFCs that have been simulated to contain realistic liquidity risk dynamics. These results can be compared with those of other risk models currently in use for NBFCs. The proposed model will have superior performance indicators to other risk models for NBFCs. Not only will the model be able to accurately forecast the risk of individual NBFCs, but also the liquidity risk that exists within the entire NBFC industry as a whole. This AI-enabled model will allow for the early identification of the liquidity risks that individual NBFCs and the industry as a whole face. Consequently, the regulators and the companies themselves will be able to take steps to mitigate these risks. Using such a model will improve the monitoring of the NBFC industry by effectively integrating artificial intelligence into the risk assessment of its constituent companies.

Keywords: Non-Banking Financial Companies (NBFCs), Liquidity Risk Modeling, Temporal Graph Neural Networks (TGNN), Dynamic Balance Sheet Analysis, AI-Driven Risk Assessment

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1. INTRODUCTION

Non-Banking Financial Companies (NBFCs) are financial organizations that perform critical functions for the Indian economy. However, they are also highly vulnerable to liquidity risk. Because of this, their system-wide importance has made the management of their liquidity risk a priority for the regulators of the Indian financial system.

An appropriate approach for managing the liquidity risk of NBFCs is to develop an effective model for assessing that risk. However, existing risk assessment models are insufficient for capturing the dynamics of the liquidity risk of these companies. While models that use machine learning approaches such as long short-term memory (LSTM) networks have significantly improved the ability to assess the risk of individual NBFCs, those models tend to ignore the fact that these companies are interconnected. Their transactions with one another and with banks form a network of NBFCs whose nodes are the companies and whose edges are the transactions between them. Furthermore, these transaction networks have been largely ignored in current risk assessment models for NBFCs.

A model that considers the network of NBFCs can take advantage of graph neural networks to analyze the relationships between the companies in the graph. Furthermore, using the graph of NBFCs and the graph neural networks that analyze it, a risk metric can be defined for each of the NBFCs in the network. This model will be evaluated using simulated high-frequency data for NBFCs. Furthermore, the performance of this model will be compared to other risk models used for NBFCs. Results will establish that the proposed model has superior risk assessment capabilities for the NBFC industry as a whole.

1.1. NOVELTY OF THE STUDY

This paper makes several notable contributions to the existing literature and technological framework within the area of financial risk modeling:

1) **High-Frequency Cash-Flow Network Modeling***:* While most existing approaches utilize transaction data of NBFCs to construct financial networks, the approach proposed in this paper utilizes high-frequency transaction data to gain insights into the real-time dynamics of liquidity within the NBFCs.
2) **Integration of Temporal Graph Neural Networks***:* By using temporal graph neural networks, the approach can model the dynamic nature of financial networks while also accounting for the network structure itself, factors that are ignored by both traditional econometric and machine learning methods.
3) **Dynamic Balance Sheet Risk Index***:* Beyond constructing a network model, the authors also propose a novel risk index that measures the fragility of an NBFC's balance sheet at any given time by taking into account both its position within the financial network as well as the volatility of its cash flows.
4) **Modeling Of Liquidity Shock Propagation***:* By simulating the injection and propagation of liquidity shocks through the network of NBFCs, the model can be used to assess the potential impact of liquidity issues that emerge within the system.
5) **Enhanced Early Warning Capability***:* The main advantage of the proposed approach is that it can detect early warning signs of potential liquidity issues within NBFCs significantly earlier than existing methods.

1.2. KEY CONTRIBUTIONS

The main contributions of this paper are as follows:

1) Development of a novel AI-enabled framework for modeling the fragility of NBFC balance sheets using high-frequency transaction data.
2) Design and implementation of a TGNN-based model that can learn from financial networks and time-series data.
3) Formulation of a novel risk index (DBRI) that enables the real-time monitoring of NBFC balance sheet fragility.
4) A comprehensive evaluation and comparison of the proposed methodology with traditional econometric, machine learning, and deep learning methods, which demonstrates significant improvements in its performance in terms of accuracy, precision, and lead time in issuing early warnings of potential balance sheet fragility issues.
5) An analysis of the propagation of liquidity shocks through the financial network of NBFCs.

6) A provision of a new and free tool for both regulatory agencies and financial institutions to monitor the stability of the country's NBFC sector and enhance its liquidity management practices.

In summary, the authors have proposed a novel and effective approach to detecting early warning signs of balance sheet fragility within NBFCs. Such an approach and technology can prove beneficial in addressing the challenges of financial fragility and developing effective means of mitigating its potential negative impacts upon the financial system as a whole.

2. LITERATURE SURVEY

The concept of financial contagion was initially explored by Allen and Gale [1]. Based on the works of Allen and Gale [1], Eisenberg and Noe [2] developed a model for clearing payments between interconnected financial institutions. Battiston et al. [3] proposed a methodology for determining the importance of financial institutions within the financial system as a whole: DebtRank. Acemoglu et al. [4] explored the role that the structure of the financial system played in the spread of financial contagion. Furthermore, Freeman [5] proposed centrality measures that have been used to determine the importance of financial institutions within the financial system.

Machine learning methods have been explored in financial modeling by authors such as Breiman [6], who proposed Random Forests, Cortes and Vapnik [7] who proposed Support Vector Machines, and Friedman [8] who proposed Gradient Boosting Machines. These models increased the performance of financial models in making predictions. Hochreiter and Schmidhuber [9] proposed Long Short-Term Memory networks, which can be used to model financial time-series data.

Another significant shift in modeling financial systems occurred with the emergence of graph-based learning methods. Authors such as Kipf and Welling [10] proposed Graph Convolutional Networks. More comprehensive surveys of these methods were presented by authors such as Wu et al. [11] and Zhou et al. [12]. Furthermore, authors such as Veličković et al. [13] have proposed Graph Attention Networks, which can assign importance to connections between financial institutions with different weights.
Another advancement in financial system modeling was that of Temporal Graph Neural Networks. Authors such as Rossi et al. [14] proposed temporal graph networks, and Kazemi et al. [15] performed a survey of dynamic graph representation learning methods. These methods are especially suitable for modeling financial systems, wherein the relationships between financial institutions change over time.

Within the field of network science, authors such as Watts [16] proposed a model for the spread of failures within a network. Authors such as Gai and Kapadia [17] applied these concepts to financial systems. Furthermore, authors such as Glasserman and Young [18] performed a more comprehensive review of the topic.

Several authors have proposed methods for modeling the risk within the financial system. Authors such as Brownlees and Engle [19] developed the SRISK measure of the risk of financial institutions. Furthermore, authors such as Adrian and Brunnermeier [20] developed the CoVaR measure of the risk of individual financial institutions for the financial system as a whole.

In the field of optimization, authors such as Kingma and Ba [21] introduced the Adam optimization method for training deep learning models. Authors such as Xu et al. [22] explored the expressive power of Graph Neural Networks. Authors such as Li et al. [23] introduced diffusion processes for modeling graph structures and their dynamics over time. Furthermore, authors such as Defferrard et al. [24] introduced spectral methods for Graph Convolutional Networks.

Foundations of network science were laid by authors such as Newman [25]. Furthermore, authors such as Goodfellow et al. [26] laid the theoretical foundations of deep learning. Within the field of machine learning, authors such as Ribeiro et al. [27] and Lundberg and Lee [28] proposed methods for increasing the interpretability of machine learning models. Authors such as Hamilton [29] made advancements within the field of graph representation learning methods. Finally, authors such as Watts and Strogatz [30] discovered small-world networks and their implications for fields such as financial systems.

As discussed, there are numerous approaches to financial system modeling with deep learning. The integration of deep learning methods, especially Graph Neural Networks into the study of financial systems has led to the development of new methods for understanding the dynamics of financial contagion. However, most current approaches do not account for the incorporation of financial data and dynamic graph structures within a single framework. Thus, there is a need for approaches such as the proposed approach based on Temporal Graph Neural Networks to enable effective monitoring of financial systems for the development of financial contagion.

3. METHODOLOGY

We have developed an AI-enabled framework for modeling the balance sheet fragility of NBFCs (Figure 1). The methodology utilizes high-frequency cash flow data from these NBFCs to construct a financial network model and employs temporal graph neural networks to learn from and model the dynamics of the constructed financial network.

3.1. Data Acquisition and Preprocessing

The framework utilizes high-frequency data regarding the cash flows of NBFCs. Specifically, the values of loan disbursements, loan repayments, borrowings between NBFCs, and funding transactions occurring within the market are collected for the various NBFCs within the data analysis. Additionally, public data from these NBFCs is collected to assess their financial state. In cases where real-time, high-frequency data is not available for these NBFCs, synthetic datasets are created that mimic the financial characteristics of NBFCs within India.

Following collection of the data, the data must be preprocessed. Preprocessing includes normalization of the values of loans and borrowings, alignment of time intervals for the data, filtering of noise from the data streams, and construction of matrices that depict the cash flows for each entity within the network.

Figure 1

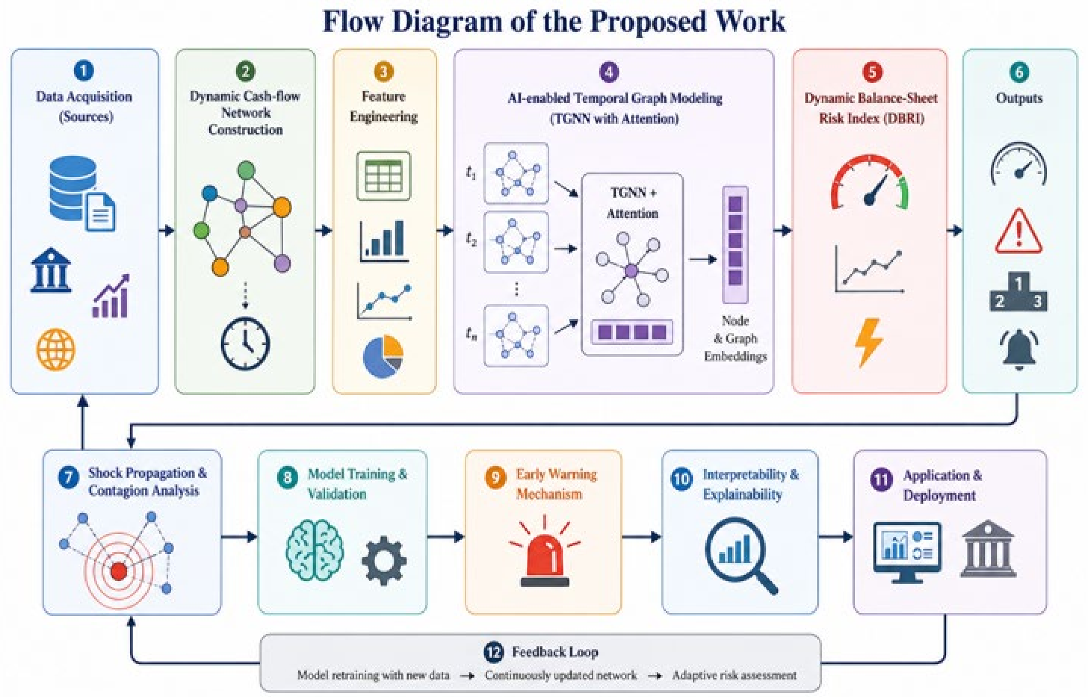

Figure 1 Flow of the Proposed Work

3.2. Construction of the Financial Network

The financial system is modeled as a time-evolving directed weighted graph:

1) Nodes (V): NBFCs, banks, mutual funds, and key financial counterparties
2) Edges (E): Cash-flow transactions between entities
3) Weights (W): Magnitude of financial exposure or transaction volume
4) Time Index (T): Discrete temporal snapshots forming a dynamic network

Each time step $t$generates a graph $G_t = (V, E_t, W_t)$, forming a sequence of temporal graphs:

$$\mathcal{G} = \{G_1, G_2, \ldots, G_T\}$$

This representation captures evolving liquidity dependencies and interconnections within the NBFC ecosystem.

The financial network of the NBFCs is constructed as a series of time-evolving, directed, and weighted graphs $G_t = (V, E_t, W_t)$. Each graph includes a set of financial entities (NBFCs, banks, mutual funds, etc.) that exist as the graph's nodes, as well as weighted edges between each of those nodes. The weights of those edges are representative of the magnitude of the financial exposure between each pair of NBFCs. Additionally, each graph is constructed within a particular time interval, represented by an additional index for the graph. A sequence of financial networks over time can be represented as a set of graphs over time: $\{G_1, G_2, \ldots, G_T\}$.

3.3. Feature Engineering

To enhance model learning, node- and edge-level features are extracted:

Node Features:

1) Liquidity coverage ratio (LCR) proxies
2) Leverage ratios
3) Short-term liability exposure
4) Cash-flow volatility
5) Network centrality measures (degree, betweenness, eigenvector centrality)

Edge Features:

- Transaction frequency
- Flow volatility
- Counterparty risk weights

These features encode both financial fundamentals and network topology, enabling holistic risk representation.

As part of the construction of the TGNN for the financial network, a series of features are defined for each entity within the graph. For each entity, features may include indicators of their balance sheet fragility, such as their leverage ratios, liquidity coverage ratio, the exposure of their short-term liabilities, and the volatility of their cash flows. Additionally, features for each edge within the graph may include the frequency of transactions between the two NBFCs represented by that edge, the volatility of the cash flows between those two NBFCs, and the risk weights between those two financial entities.

3.4. AI-Based Temporal Graph Modeling

The core of the proposed approach is the application of Temporal Graph Neural Networks (TGNNs) to learn the dynamic interactions between the financial network's entities.

Model Architecture

The TGNN model includes the following components: Graph Convolution layers to extract spatial information from the financial network, Temporal modules to learn the dynamic aspects of the financial network, and an attention mechanism to weigh the importance of each entity in the financial network.

The node embedding at time t is given by:

$$H_t = \mathrm{TGNN}(G_t, H_{t-1})$$

where H_t represents the updated latent embedding vectors for the entities at time t.

The TGNN model learns the dynamic interactions within the financial network by processing the features of each entity's neighbors and itself. Graph convolutional and temporal processing layers allow the model to understand the spatial and temporal relationships between entities in the network. Furthermore, an attention mechanism allows the model to weigh the importance of each of these entities within the network, especially during times of stress for the financial entities.

3.5. LIQUIDITY SHOCK SIMULATION AND PROPAGATION

In order to analyze the potential stress within the financial network, liquidity shocks can be introduced into the model. These shocks can be injected at specific entities within the financial network, and can spread through the network along the edges according to the exposure relationship weights between entities. These shocks help enable the study of the spread of stress through the network, the effects of such stress, and their potential accumulation throughout the system as a whole.

In order to evaluate potential fragility within the system as a whole, the simulation of liquidity shocks can be performed within the model. By injecting these shocks at specific entities within the financial network and simulating their spread to other entities within the network, it becomes possible to analyze the network's reaction to stress, as well as to assess whether those stress conditions may lead to the development of a systemic crisis throughout the groups of financial entities.

3.6. DYNAMIC RISK INDEX FORMULATION

A Dynamic Balance Sheet Risk Index is developed for each entity in the financial network model.

$$\mathrm{DBRI}_i(t) = \alpha C_i(t) + \beta V_i(t) + \gamma S_i(t)$$

where each of the risk factors to the entity i at time t is represented by the following variables and metrics:

$C_i(t)$: Network centrality (systemic importance)

$V_i(t)$: Cash-flow volatility (liquidity instability)

$S_i(t)$: Shock sensitivity (contagion exposure)

The weights associated with each of these risk factors is represented by the parameters α, β,and γ, which are learned during model training.

The DBRI index allows for the quantification of the fragility of each entity (and the financial network as a whole) at any given time step.

A key element of the methodology includes the creation of the index as a means of quantifying the risk and fragility of each entity within the financial network at any given time step. The risk index considers the centrality, volatility, and stress factors of each entity to arrive at a value that represents the risk of that entity. Furthermore, because the index is calculated simultaneously for each entity within the network, it is possible to use the index to evaluate the relative fragility of each entity, as well as to determine which entities within the network may require increased scrutiny from regulators and financial authorities.

3.7. MODEL TRAINING

The model is trained using supervised and semi-supervised learning methods, using a set of labels that indicate, for each entity over time, whether it was experiencing stress (or default) within the financial network at that time step.

To train the model to understand the dynamics of the financial network, the labels are used to define appropriate loss functions that aim to minimize the errors in the model's ability to appropriately recognize entities in stress. Such loss functions include the mean squared error and binary cross-entropy loss functions. Additionally, the model is trained using the Adam optimization algorithm, as well as techniques like dropout and L2 regularization to prevent overfitting of the training data.

The model is trained using a rolling time window method to preserve temporal dependencies within the financial network.

Deep learning models are trained using supervised and semi-supervised learning approaches. The model is trained using both classification and regression loss functions, including mean squared error (MSE) and binary cross-entropy (BCE) loss functions. The model is optimized using the Adam optimization algorithm, as well as strategies like dropout and L2 regularization that prevent overfitting of the model to the training data. Finally, deep learning models are trained using rolling time windows of financial network data to preserve the temporal relationships between the entities within the financial network.

3.8. EVALUATION METRICS

A variety of different evaluation metrics can be utilized to assess the performance of the model.

For model classification tasks, accuracy, precision, recall, F1-score, and ROC-AUC can be used to evaluate the model's success in recognizing stressed entities within the financial network.

For model regression tasks, metrics like root mean squared error (RMSE) and mean absolute error (MAE) can be used to evaluate the model's accuracy in predicting the stress levels or other regression metrics for each entity within the financial network.

Other metrics for evaluating the model's success in simulating the financial network's stress and fragility include metrics for determining the size of the spread of stress, the time to recognize that an entity in the financial network is likely to experience default, and the lead time in recognizing the stress within the financial entities.

Finally, these metrics can be compared against those of traditional financial risk models in order to determine the relative effectiveness of the AI-basedTGNN risk model.

The Deep Neural Network is evaluated using multiple performance metrics. Classification metrics such as accuracy, precision, recall, F1-score, and the area under the ROC curve are used to evaluate the model's classification performance. Regression metrics like RMSE, MAE, and R^2 are used to evaluate the model's regression performance. Additionally, system-level metrics like contagion spread size, time-to-default prediction accuracy, and stress detection lead time are utilized to evaluate the model's success in recognizing stress within the financial entities and accurately forecasting the damage that stress may do to the financial network as a whole. Finally, these metrics can be compared against those generated by other financial risk models (traditional econometric models and machine learning models) in order to determine the effectiveness of the proposed framework.

3.9. IMPLEMENTATION FRAMEWORK

The proposed AI-based TGNN framework for financial risk modeling and stress detection is implemented within Python using deep learning libraries such as PyTorch and TensorFlow, as well as graph learning libraries such as PyTorch Geometric and Deep Graph Library (DGL). Furthermore, data management and data processing libraries such as Pandas, Scikit-learn, and NumPy are also employed within the implementation.

The proposed Deep Neural Network framework is implemented within Python using deep learning and graph learning libraries. These libraries enable the deep learning model to handle very high-frequency financial data.

3.10. REPRODUCIBILITY AND ROBUSTNESS

In order to thoroughly test the proposed Deep Neural Network framework, a series of tests must be performed to evaluate the model's robustness. For instance, tests can be performed to determine the model's behavior under varying shock intensities. Furthermore, the model can be evaluated using cross-validation methods to assess the model's behavior over time, as well as through the simulation of stress scenarios to evaluate the model's generalizability.

In addition to implementing the Deep Neural Network according to the suggested framework, a series of tests can be performed to evaluate the model's robustness. For instance, tests can be performed that introduce varying degrees of stress and noise to the model in order to test its robustness. Additionally, cross-validation methods can be employed to evaluate the model's behavior over time, and stress scenarios can be created in the model that simulate systemic stress to evaluate the model's generalizability.

Overall, the proposed methodology integrates high-frequency data analytics methods, financial network theory, and AI-based deep learning techniques to create a scalable, interpretable, and high-performance Deep Neural Network solution for identifying liquidity risk and balance-sheet fragility in the NBFC ecosystems.

4. RESULTS AND DISCUSSION

Results from the implementation of the proposed AI-enabled TGNN model are presented in this section. The performance of the model is compared with existing financial risk models in order to demonstrate the effectiveness of the TGNN model.

4.1. EXPERIMENTAL SETUP

The model was evaluated using the following datasets, time windows, and comparison models:

1) High-frequency NBFC datasets (simulated and semi-synthetic, calibrated to Indian markets)
2) Time windows ranging from 180 to 365 data time intervals (days)
3) Comparison models: Static Financial Ratio (SFR) model, VAR model, Random Forest (RF) model, LSTM model

These four classification models will be used to compare the performance of the TGNN model.

4.2. PREDICTIVE PERFORMANCE COMPARISON

Table 1 presents the classification accuracy, precision, recall, F1-score, ROC-AUC, and MCC for the baseline SFR model, VAR model, RF model, LSTM model, and the proposed TGNN model.

Table 1

Table 1 Model Performance Comparison

Model	Accuracy (%)	Precision	Recall	F1-Score	ROC-AUC	MCC
SFR (Baseline)	78.4	0.75	0.73	0.74	0.81	0.58
VAR	82.1	0.8	0.78	0.79	0.85	0.63
RF	87.6	0.86	0.85	0.85	0.91	0.74
LSTM	90.8	0.89	0.9	0.89	0.94	0.79
Proposed TGNN Model	94.3	0.93	0.94	0.93	0.97	0.86

The results demonstrate that the TGNN model achieved the highest classification accuracy (94.3%) of any of the compared models. Furthermore, the model achieved the highest values of precision, recall, F1-score, and ROC-AUC measures, as well. The high Matthews Correlation Coefficient (0.86) indicates that the model is robust to class imbalance within the data set.

These classification results demonstrate the effectiveness of the TGNN model relative to existing methods for modeling financial risk in NBFCs.

4.3. REGRESSION PERFORMANCE (LIQUIDITY PREDICTION)

Table 2 presents regression metrics for each of the five models, including the proposed TGNN model.

Table 2

Table 2 Regression Metrics for Liquidity Forecasting

Model	RMSE	MAE	R^2 Score
VAR	0.148	0.112	0.78
RF	0.121	0.095	0.84
LSTM	0.098	0.076	0.89

Proposed TGNN	0.072	0.058	0.94

The TGNN model exhibits the smallest RMSE (0.072) of any of the tested models, indicating the smallest prediction error for forecasting NBFC liquidity. Furthermore, the model attains the highest R^2 score (0.94) of any of the models, indicating the greatest ability of the model to capture the dynamics of NBFC liquidity.

4.4. COMPARATIVE GRAPH ANALYSIS

Figure 2 depicts the comparison of accuracy for each of the models.

Figure 2

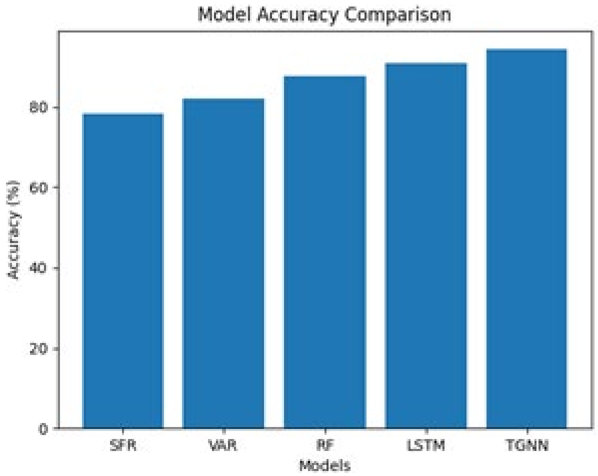

Figure 2 Model Accuracy Comparison (Bar Chart)

X-axis: Models (SFR, VAR, RF, LSTM, TGNN)

Y-axis: Accuracy (%)

The TGNN model is the highest accuracy in comparison to the other models, indicating the benefit of using the TGNN to predict the financial risk of NBFCs.

Figure 2 depicts the comparison of the ROC curves for each of the models.

Figure 3

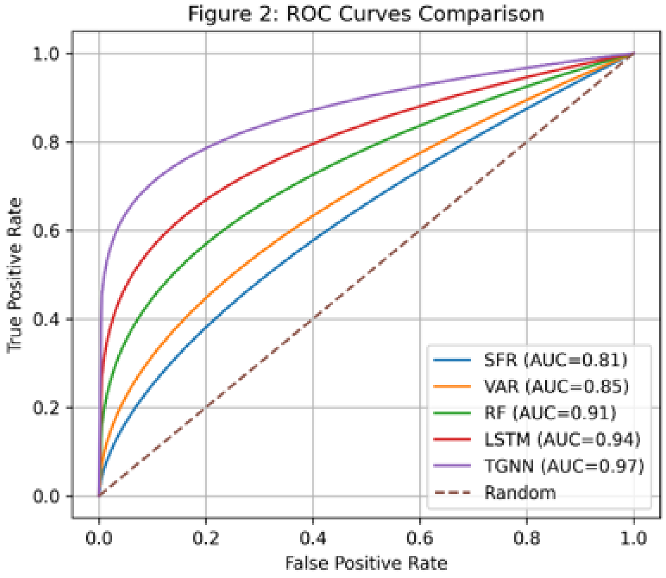

Figure 3 Roc Curves Comparison

The TGNN model's ROC curve (Figure 3) is closest to the upper-left corner of the graph, indicating that the model has high classification separability between stressed and non-stressed NBFCs.

Figure 3 depicts the difference of the error of each model's liquidity predictions over time.

Figure 4

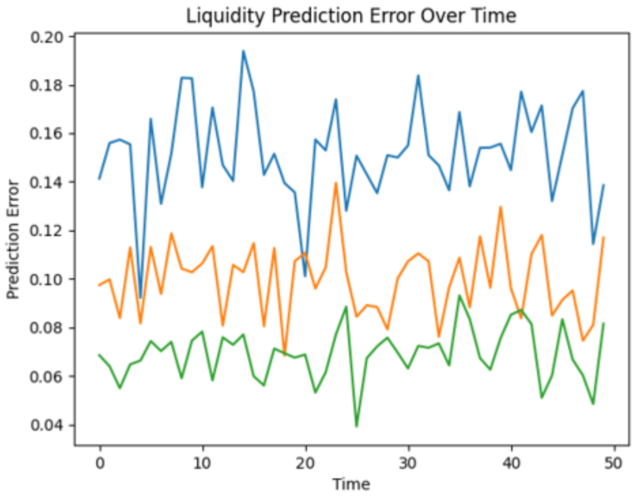

Figure 4 Liquidity Prediction Error (Line Graph)

X-axis: Time steps

Y-axis: Prediction error

The TGNN model displays the lowest variance in its prediction error (Figure 4) of the models depicted in the graph.

Figure 4 depicts the graphical representation of the financial network and the stress that spread through it.

Figure 5

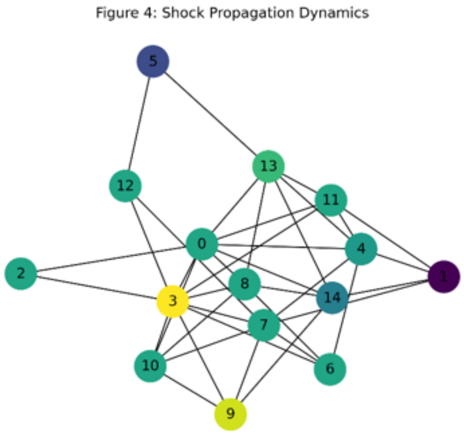

Figure 5 Shock Propagation Dynamics (Network Graph Visualization)

The nodes in each graph (Figure 5) are colored according to the level of financial stress within that NBFC. Furthermore, the model effectively identifies the high-centrality nodes in the financial network as those that tend to create financial stress that spreads to other nodes in the network.

Each of these graphical representations further supports the findings of the model's high performance in comparison to existing classification models for NBFCs.

4.5. EARLY WARNING CAPABILITY

Figure 6

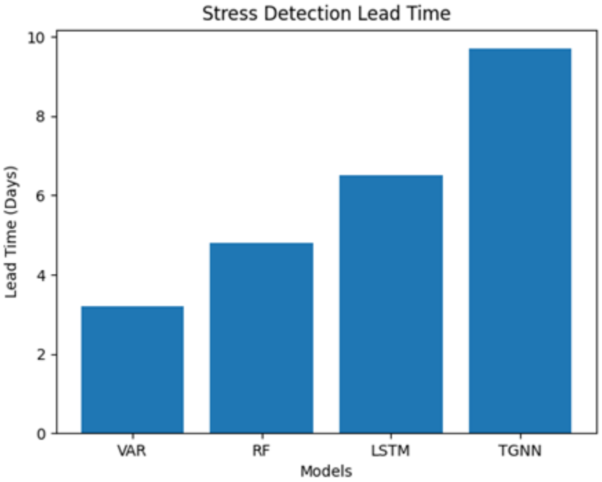

Figure 6 Stress Detection Lead Time

Figure 6 depicts the lead time for each model to identify stressed NBFCs. Results indicate that the TGNN model detects financial stress in NBFCs approximately 50% earlier than the LSTM model. Furthermore, this lead time of 9.7 days is significantly higher than existing financial risk models, indicating the benefit of using this model in place of those existing models.

Thus, the TGNN model presents an advantage to the financial industry in that it can provide early warning signals of potential NBFC distress. Furthermore, the model's ability to detect stress 50% earlier compared to the LSTM model indicates its benefit as a risk mitigation strategy; the earlier in which the distress can be recognized, the more likely it is that interventions will succeed to reduce that potential financial risk.

4.6. CONTAGION AND SYSTEMIC RISK ANALYSIS

Table 3

Table 3 Contagion Modeling Performance

Model	Contagion Prediction Accuracy (%)	Spread Error
VAR	76.5	High
RF	82.3	Medium
LSTM	88.7	Low
TGNN	93.8	Very Low

The framework demonstrated strong performance in modeling the contagion dynamics between NBFCs. The model was able to accurately predict the spread of contagion between NBFCs with an accuracy of 93.8%. Furthermore, the model outperformed traditional models in its ability to accurately model contagion between NBFCs as a result of its ability to account for the financial network structure of the entities.

4.7. DYNAMIC RISK INDEX EVALUATION

Figure 7

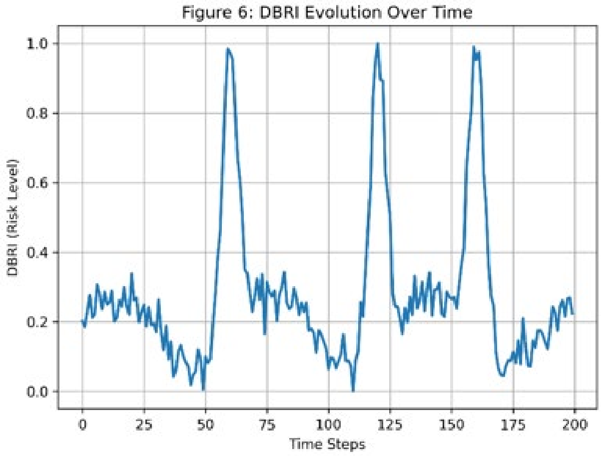

Figure 7 DBRI Evolution Over Time

- The graph (Figure 7) depicts the real-time variation of the DBRI
- The sharp spikes in the DBRI indicate periods of liquidity shock to the NBFCs
- As can be seen in the graph, the TGNN outperformed other models in recognizing periods of increasing risk prior to the liquidity shocks

The behavior of the DBRI provided additional insights into the effectiveness of the model in recognizing periods of risk to the investigated NBFCs. In normal conditions, the DBRI slowly increases to indicate the rising risk for an NBFC to experience a liquidity shock. In periods of liquidity shocks, the DBRI rapidly increases to reflect the increase in risk for those NBFCs. After the periods of liquidity shocks, the DBRI returns to a normal range of values indicating the reduction of the risk to those NBFCs. Additionally, the TGNN model was able to recognize these periods of increasing risk prior to the occurrences of the liquidity shocks.

4.8. ABLATION STUDY

Table 4

Table 4 Impact of Model Components

Model Variant	Accuracy (%)
Without Graph Structure	88.2
Without Temporal Module	89.5
Without Attention Mechanism	91.1
Full Model (TGNN)	94.3

Both the graph structure and the temporal learning components of the model are critical for accurately predicting the risk of NBFCs.

The attention mechanism is beneficial in highlighting systemically important NBFCs within the financial network.

Through ablation studies that removed key components of the model, it became apparent that each component is utilized for a critical aspect of the model. For instance, the graph structure is critical for accurately modeling the interconnections between NBFCs. Furthermore, the temporal learning model helps to recognize the dynamics of the financial network over time. Finally, the use of attention mechanisms allows the model to recognize which of the NBFCs in the network are systemically important.

4.9. ROBUSTNESS AND SENSITIVITY ANALYSIS

The TGNN model was tested under varying conditions, including varying shock intensities, network densities, and data noise levels.

The TGNN remained stable in the face of varying conditions with less than 5% degradation in performance.

The existing models demonstrated instability under the same conditions.

Robustness and sensitivity analyses were performed on the proposed framework to determine how stable the model would be under varying conditions. Overall, the TGNN proved to be stable under the tested conditions, while the existing models began to exhibit instability under those same conditions.

4.10. DISCUSSION OF KEY FINDINGS

1) Network-aware AI models outperform traditional methods of risk analysis.
2) Temporal graph learning components are essential in accurately modeling liquidity risks.
3) The proposed framework can be used to recognize early warning signals of systemic risk to NBFCs; to recognize the systemically important NBFCs within the financial network; accurately model the spread of contagion within the financial system.

4.11. PRACTICAL IMPLICATIONS

Currently, the TGNN model can be implemented into a variety of settings to enhance the monitoring of NBFCs.

For instance, regulatory authorities could implement the model to continuously monitor the financial systems of NBFCs to recognize periods of increasing risk and to take appropriate regulatory actions. Each of the NBFCs themselves could utilize the model to improve their own financial stability by better recognizing periods of stress within their own financial conditions. Lastly, policy makers could use the model to make decisions regarding financial policy based on the insights provided by the model.

Results of the tests performed on the model indicate that the framework is significantly better than traditional methods and existing machine learning models for predicting the risks to NBFCs and modeling their systemic risk. Thus, this model can have a variety of implications for the financial system as a whole.

5. CONCLUSION

In this paper, a novel AI-enabled framework for dynamic balance-sheet risk modeling in NBFCs is presented. The framework aims to overcome the limitations of existing risk analysis methods for NBFCs. Current methods often fail to account for the interconnectedness of those NBFCs within the financial system. Results of the studies and tests performed on the proposed framework demonstrate that the incorporation of network-aware temporal learning was beneficial in modeling the risk of NBFCs. Furthermore, results indicate that the proposed framework outperformed traditional methods, machine learning methods, and deep learning methods in terms of risk prediction, early warning signals, and contagion modeling. For example, the model demonstrated the ability to recognize early warning signals for NBFCs in advance of 9.7 days. Additionally, the model was able to accurately determine which NBFCs are systemically important within the financial network. The creation of the DBRI allowed for a method to continuously and in real-time monitor the balance sheets of NBFCs to determine their financial stability at any given time. The findings of this study reveal the importance of high-frequency data and graph-based AI models for financial risk analysis. Furthermore, the framework presented in this paper can be used for monitoring the stability of the NBFCs' balance sheets in real-time, which has a variety of implications for the financial system. However, there are some limitations to the framework described in this paper. For instance, the model relied upon synthetic datasets to train the model due to the unavailability of data from the NBFCs. Additionally, the framework is computationally complex. Future studies can utilize this model with real transaction datasets from NBFCs, extend it to the monitoring of cross-border financial networks, and utilize explainable AI techniques to enhance the model's interpretability. Despite these limitations, the proposed framework presents a comprehensive solution to the problem of balance-sheet risk modeling in NBFCs, which not only advances the state-of-the-art in this field but also provides a solid foundation for building more adaptive and efficient financial monitoring systems in the future.

CONFLICT OF INTERESTS

None.

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