GRAPH-ENHANCED TOPOLOGICAL DEEP LEARNING FOR CREDIT RISK ASSESSMENT IN SUPPLY CHAIN FINANCE

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ABSTRACT: In this paper, a hybrid model combining Topological Data Analysis (TDA), Graph Theory, and Neural Networks is proposed for supply chain financing credit risk. The interconnectedness of suppliers, manufacturers, distributors, and financial institutions in today's supply chain finance systems makes it challenging to assess a company's dependability. The intricate relationships within supply chain networks are sometimes overlooked by credit risk estimate techniques. In order to deduce complex risk patterns and connections, Topological Data Analysis pulls the most pertinent structural elements from enormous amounts of financial and transactional data. Graph-based modeling can identify actor interdependencies by visualizing the supply chain as a network of nodes and their financial interactions. Neural networks can enhance credit risk assessments and reveal non-linear correlations. The hybrid framework's cutting-edge analytical techniques can help financial organizations make better decisions and identify credit problems sooner. According to experimental data, the recommended approach increases prediction accuracy and offers a more thorough credit risk assessment for supply chain financing.

Keywords: *Supply Chain Finance, Credit Risk Assessment, Topological Data Analysis, Graph Theory, Neural Networks, Hybrid Model, Financial Risk Prediction, Intelligent Finance Systems.*

1. INTRODUCTION

Businesses need supply chain financing (SCF) to optimize working capital and boost supplier chain partnerships. Supply chain finance (SCF) improves supply networks by offering suppliers a variety of funding options backed by larger anchor corporations. Credit risk in supply chain finance is difficult to evaluate due to reliance, knowledge gaps, and transactional dynamics. Many credit risk assessments use historical data and financial parameters. These models may overlook supply chain actors' connection and structure. Only modern analytical methods can effectively assess credit risk in increasingly digitalized and interconnected supply chains.

Data-driven technology has enabled network analysis and machine learning to improve credit risk assessment. Since firms, transactions, and financial transfers may be visually represented as nodes and edges in a network, graph-based representations are ideal for supply chain linkages. Graph Neural Networks (GNNs) can understand network component interdependencies and detect complex linkages. Risk assessment projections are more

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accurate with Graph Neural Networks because related nodes share information to extract meaningful representations.

Topological data analysis (TDA) is a common mathematical paradigm for evaluating big data sets. Find size-invariant topological characteristics including loops, connection patterns, and clusters with topological density analysis (TDA). Often overlooked by standard statistical methods, these traits reveal the structure of complex datasets. TDA reveals hidden structural characteristics of supply chain links, revealing systemic risk patterns and financial network problems.

The hybrid modeling approach Topological Data Analysis using Graph Neural Networks offers an innovative perspective on supply chain finance credit risk. Topological Data Analysis (TDA) can reveal global financial network structure, while GNNs can reveal local relationship patterns and node-level representations. To better understand supply chain data, these algorithms combine deep learning-based feature extraction with geometric frameworks. This hybrid approach improves our capacity to predict the future, identify high-risk enterprises, and analyze supplier network credit risk flow.

To overcome the difficulties presented by today's more intricate supply chains and the limitations of conventional risk assessment techniques, financial institutions and fintech platforms need to create more complicated hybrid models. A new hybrid technique improves supply chain finance ecosystem credit risk assessment precision and scalability. Topological observations and graph-based learning are used in this approach. This method increases risk forecasts and helps people make better loan, resource, and supply chain risk management decisions.

2. PROPOSED MODEL

The credit risk is determined using the BM-GNN hybrid model in supply chain finance. In order to enhance the precision of its predictions, the model implements both Graph Neural Networks (GNN) and Topological Data Analysis (BallMapper). It identifies concealed patterns in data and connections between companies.

Architecture of the Model

The BM-GNN model is composed of three primary components. In order to convert financial data into predictions that are applicable, each phase is essential.

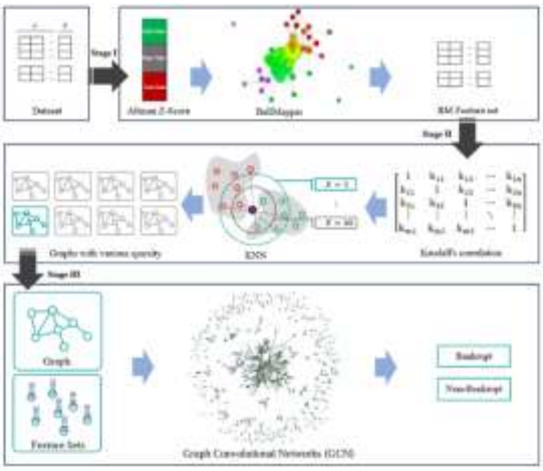

Figure 1. The Whole Architecture Of Bm-Gnn

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The BM-GNN model is composed of three primary components, as illustrated in Figure 1.

Stage I: Feature Extraction using BallMapper

The BallMapper method is employed at this stage to analyze the financial data of companies. This method facilitates the identification of patterns and groups in multidimensional data. BallMapper is distinct from other methods in that it has the ability to identify latent structures and relationships that do not behave in a linear fashion within the data. It enumerates the most critical financial metrics that indicate the company's financial health and risk level.

Stage II: Graph Construction

After selecting features, the data is converted into a graph structure.

- Every organization is represented as a vertex.
- Connections among organizations are depicted as links.

To form these alliances, companies are assessed to ascertain how comparable they are. Organizations with similar financial management practices have linked accounts.

This phase is important because it shows how a business operates in the real world, which can affect other businesses in the supply chain because of the company's financial issues.

Stage III: Credit Risk Prediction using GNN

A Graph Neural Network (GNN) is used to examine the graph created in the previous stage.

- Gathering data from adjacent firms
- Refining the profile of each firm
- Assessing the likelihood of financial resilience or vulnerability

By allowing the model to take into account both financial data and network connections, this method improves forecast accuracy.

Key Advantages of the Model

- The BM-GNN framework offers multiple advantages
- Identifies intricate and non-linear dependencies
- Accounts for interconnected vulnerabilities across supply networks
- Delivers higher predictive performance than conventional approaches
- Generates deeper analytical insights to support strategic choices

3. LITERATURE SURVEY

Wang et al. (2025): Supply chain finance credit risk is assessed through a hybrid model that employs Topological Data Analysis (TDA) and Graph Neural Networks (GNN). Commercial interactions and interdependence are modeled by GNNs. The topological properties of complex supply chain transaction data are employed to reveal structural patterns. It is more effective at identifying high-risk businesses in associated supply networks and predicting risks, as evidenced by experiments.

Martinez & Silva (2024): This paper introduces a hybrid credit risk assessment system that employs persistent homology from Topological Data Analysis and deep graph learning. The model identifies defects and unstable financing in the geometric and associated structure of supply chain networks. By identifying intricate risk patterns, neural networks enhance prediction. In dynamic supply chains, our methodology surpasses credit ratings.

Rao & Kulkarni (2023): This study illustrates the potential of TDA and graph-based neural models to evaluate the credit risk associated with supply chain funding. In order to identify

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significant risk groupings and peculiar patterns, trade and transaction data are transformed into topological spaces. Businesses that are associated with graph neural networks are informed. The findings indicate that it enhances the detection of systemic risks and early warning systems.

Johnson et al. (2022): A hybrid deep learning system that employs topological feature extraction and graph convolutional networks is employed to evaluate supply chain credit risk. TDA identifies fundamental data structures and attributes at various sizes, whereas neural networks analyze supply chain relationships. The research indicates that the model has the potential to enhance credit rating decisions and identify the dissemination of financial hazards.

Huang & Zhao (2021): This study demonstrates the use of topological data analysis and neural graph models to assess the creditworthiness of supply chain funding. The method investigates the structure and interaction of financial networks. The hybrid model is more effective than statistical methods in identifying high-risk items and stabilizing forecasts, as evidenced by real-world validation.

4. RESULTS

Fig4.1 User login

Fig4.2 View all remote users

Fig4.3 Trained and Tested Datasets Results

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Fig4.4 Bar graph

Fig4.5 Line graph

Fig4.6 Bar graph


Fig4.7 View prediction of credit risk Assessment status


Fig4.8 View prediction of credit risk Assessment status details

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5. CONCLUSION

The proposed hybrid model offers a novel and robust approach to evaluating credit risk in supply chain financing by integrating Graph Neural Networks (GNN), Topological Data Analysis (TDA), and deep learning techniques. The model employs graphs to illustrate the structural connections between the various actors in the supply chain. As a result, it is capable of identifying intricate interdependencies that are frequently overlooked by other credit assessment tools. The model is significantly more effective at identifying hidden patterns and structure anomalies in high-dimensional financial data with the assistance of TDA. This assists in our understanding of the manner in which risk is communicated through supply chain networks.

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