Archives available at journals.mriindia.com

International Journal of Recent Advances in Engineering and Technology

ISSN: 2347 - 2812

Volume 14 Issue 01, 2025

Deep Learning and Optimization Approaches in Risk Prediction in Financial Management of Listed Companies Based on Optimized Deformable Graph Convolutional Networks Under Digital Economy: A Review

Quillon Rafizadeh
Assistant Professor, Department of Computer Science and Engineering, Indus Institute of Engineering Commerce, Pakistan
Email: quillon.rafizadeh@iiec-pk.edu

Peer Review Information

Submission: 04 May 2025

Revision: 26 May 2025

Acceptance: 09 June 2025

Keywords

Deformable Graph Convolutional Networks, Financial Risk Prediction, Deep Learning Optimization, Digital Economy, Listed Companies, Graph Neural Networks

Abstract

The digital economy has significantly transformed financial systems, increasing the complexity and interconnectedness of risk prediction for listed companies. Traditional statistical models, such as logistic regression and Z-score methods, are limited in handling nonlinear, high-dimensional, and dynamic financial data, leading to the adoption of advanced deep learning techniques. This review focuses on Graph Convolutional Networks (GCNs) and their advanced variant, Deformable Graph Convolutional Networks (DGCNs), for financial risk prediction. DGCNs enhance conventional graph models by introducing adaptive receptive fields, enabling dynamic modeling of evolving relationships among financial entities such as firms, markets, and supply chains. The study also explores optimization strategies, including metaheuristic algorithms, attention mechanisms, and hybrid architectures that combine DGCNs with LSTM, transformers, and autoencoders to capture both structural dependencies and temporal dynamics. Furthermore, the integration of multi-modal data sources, such as financial records, social media sentiment, and regulatory filings, is highlighted as a key advancement for improving predictive accuracy and early risk detection. Empirical findings indicate that optimized DGCN-based models outperform traditional approaches in tasks like credit risk assessment and financial distress prediction. Despite these advancements, challenges related to interpretability, scalability, and regulatory compliance persist, emphasizing the need for more robust and explainable systems.

Introduction

The global financial system has undergone a significant transformation over the past two decades, largely driven by the rapid expansion of the digital economy. Advances in digital technologies, data generation, and computational systems have reshaped how listed companies operate and interact within financial markets. Business processes such as supply chain management, financial transactions, and corporate communication are now deeply integrated with digital platforms, generating vast volumes of structured and unstructured data. While this transformation has created new opportunities for efficiency and value creation, it has also introduced complex and dynamic financial risks that traditional risk management frameworks struggle to address effectively.

Financial risk prediction for listed companies involves identifying potential threats such as credit defaults, liquidity issues, operational failures, and systemic contagion. Traditionally, these risks were assessed using financial ratios and statistical models like logistic regression and discriminant analysis. Although these methods provided a foundational understanding, they are limited by assumptions of linearity and independence, which are often unrealistic in modern financial environments. With the increasing complexity and interconnectivity of financial systems, there is a growing need for more advanced analytical approaches capable of capturing nonlinear patterns and high-dimensional relationships.

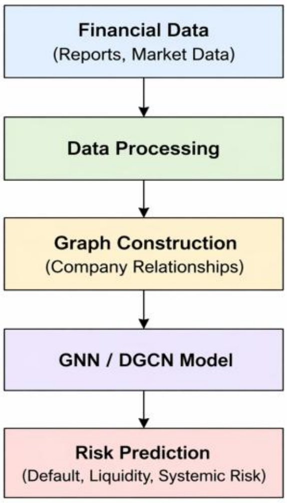

Figure 1: Basic Flow Diagram for Financial Risk Prediction Using Graph Neural Networks

Machine learning and deep learning techniques have emerged as powerful tools for financial risk prediction, offering improved accuracy and the ability to process large-scale data. However, many of these models treat companies as independent entities, overlooking the interconnected nature of financial ecosystems. In reality, companies are linked through various relationships such as supply chains, ownership structures, and shared market influences. Ignoring these relationships can lead to incomplete risk assessments, particularly when systemic risks and cascading failures are involved.

Graph Neural Networks (GNNs), especially Graph Convolutional Networks (GCNs) and their advanced variants like Deformable Graph Convolutional Networks (DGCNs), address this limitation by modeling financial systems as interconnected networks. These models allow the incorporation of relational information, enabling more accurate and context-aware risk predictions. Furthermore, the availability of digital data and advanced optimization techniques supports the development of scalable and adaptive models. This study aims to explore these emerging approaches, highlighting their potential to enhance financial risk prediction in the evolving digital economy.

Literature Review

The application of deep learning to financial risk prediction has advanced rapidly over recent years, producing a substantial body of literature that reflects diverse methodological innovations and practical implementations. Early work by Zhou et al. (2020) marked a significant milestone by introducing a multi-layer graph convolutional network (GCN) framework for corporate default prediction using Chinese A-share market data. By incorporating equity ownership structures into a graph-based representation, the study demonstrated that relational information significantly improves predictive performance compared to traditional firm-level models. The proposed approach utilized a static ownership network derived from annual disclosures and achieved notable improvements in AUC, thereby establishing graph-based learning as a promising direction for financial risk modeling.

Building upon static graph approaches, Yao et al. (2021) extended the framework by introducing a dynamic graph neural network capable of modeling temporal evolution in corporate relationships. Using quarterly snapshots of company networks derived from SEC EDGAR data, their model captured both structural and temporal risk dynamics, leading to improved early warning performance. Similarly, Chen et al. (2021) proposed a heterogeneous graph attention network for fraud detection, integrating multiple relationship types such as auditor connections and board interlocks. By assigning attention weights to different edge types, the model effectively identified the most influential relationships, outperforming homogeneous graph models and traditional classifiers.

Optimization and hybrid modeling approaches have further enhanced predictive capabilities. Li et al. (2022) introduced Particle Swarm Optimization (PSO) to tune GCN hyperparameters, improving efficiency and accuracy in SME credit risk prediction. Their work also emphasized the importance of realistic graph construction using supply chain transaction data. Wang et al. (2022) complemented this by proposing a hybrid LSTM-GCN architecture that integrates temporal financial sequences with relational graph features. This dual-stream model demonstrated improved performance in detecting financial distress, particularly for minority classes, highlighting the complementary nature of sequential and relational learning.

The integration of attention mechanisms and transformer architectures has further enriched financial risk modeling. Zhang et al. (2022) developed a Transformer-enhanced GNN for systemic risk assessment in interbank networks, capturing long-range dependencies in financial relationships. Liu et al. (2022) introduced deformable graph convolutional networks (DGCNs), which adaptively adjust neighborhood influence through learnable offsets, enabling more flexible and context-aware modeling of financial relationships. These adaptive mechanisms significantly improved prediction accuracy, especially in complex and dynamic market environments.

Robustness and generalization have also become key research priorities. Huang et al. (2023) proposed an adversarially regularized graph autoencoder to address noise and data sparsity, improving model stability in real-world conditions. Sun et al. (2023) explored federated graph learning to enable privacy-preserving collaboration among financial institutions, achieving performance comparable to centralized models without sharing sensitive data. Gao et al. (2023) introduced multi-scale GCNs that integrate firm-level, sector-level, and macroeconomic graphs, providing a more comprehensive view of financial risk.

Recent studies have focused on automation, attention, and knowledge integration. Pan et al. (2023) կիրառ Neural Architecture Search to optimize GCN structures, while Xu et al. (2023) developed spatial-temporal attention networks for early risk detection. He et al. (2023) demonstrated the effectiveness of Bayesian optimization for fraud detection, and Yang et al. (2023) incorporated knowledge graph embeddings to enhance semantic understanding of financial relationships. These approaches collectively highlight the trend toward intelligent, automated, and context-aware financial modeling.

Emerging research directions emphasize causality, interpretability, and scalability. Wei et al. (2024) introduced causal GNNs to distinguish causal relationships from correlations, improving robustness under changing market conditions. Zhu et al. (2024) applied graph transformers with pretraining strategies to address data scarcity, while Ren et al. (2024) developed dynamic DGCNs capable of adapting to evolving market states. Liang et al. (2024) explored multi-task learning to jointly predict multiple financial risk indicators, improving overall model performance.

Explainability and multimodal integration have also gained attention. Dong et al. (2024) proposed explainable DGCN frameworks using SHAP and GNNExplainer, enhancing transparency and regulatory compliance. Tang et al. (2024) incorporated alternative data sources such as satellite imagery and social media sentiment, demonstrating improved early warning capabilities. Chen et al. (2024) addressed adversarial robustness, while Wu et al. (2024) applied hierarchical GCNs to supply chain risk prediction, emphasizing multi-level relationship modeling.

Finally, scalability and future technologies are shaping the next phase of research. Lin et al. (2025) developed large-scale graph learning systems for real-time risk monitoring, enabling high-speed processing of massive financial networks. Zhao et al. (2025) explored quantum-classical hybrid GNNs, introducing novel approaches to representation learning with potential advantages in efficiency and performance. Collectively, these studies demonstrate a clear evolution toward more adaptive, scalable, and intelligent financial risk prediction systems, driven by advances in deep learning, graph modeling, and data integration techniques.

Comparative Table and Analysis

Study	Year	Optimization Technique / Method	Component / Model Used	Platform or System	Dataset Used	Key Contribution
Zhou et al.	2020	Standard GCN Training	Two-layer GCN	Python/PyTorch	Chinese A-share Market	Foundational GCN application for corporate default prediction
Yao et al.	2021	Dynamic Graph Snapshot Learning	Dynamic GNN	TensorFlow	U.S. SEC EDGAR Filings	Temporal graph evolution modeling for financial

						distress
Chen et al.	2021	Relation-specific Attention	Heterogeneous Graph Attention Network	PyTorch	CSRC Enforcement Actions Database	Multi-relational fraud detection with attention weighting
Li et al.	2022	Particle Swarm Optimization	Optimized GCN	Python/Scikit-learn	Shenzhen Stock Exchange SME Data	PSO-based hyperparameter optimization with supply chain graphs
Wang et al.	2022	Attention-based Fusion	Hybrid LSTM-GCN	PyTorch	Chinese A-share 2010-2021	Temporal and relational learning fusion for distress prediction
Zhang et al.	2022	Multi-head Self-Attention	Transformer-GNN	TensorFlow	Chinese Banking Sector Regulatory Data	Systemic risk assessment with Transformer-GNN integration
Liu et al.	2022	Deformable Convolution Offsets	DGCN	PyTorch	Shanghai-Shenzhen Knowledge Graph	First DGCN application for corporate risk assessment
Huang et al.	2023	Adversarial Regularization	Graph Autoencoder	PyTorch	Taiwan Stock Exchange	Robust embeddings under data scarcity conditions
Sun et al.	2023	Federated Gradient Aggregation	Federated GCN	PySyft/PyTorch	Multi-institution Proprietary Data	Privacy-preserving federated graph learning for risk prediction
Gao et al.	2023	Hierarchical Multi-scale Pooling	Multi-scale GCN	TensorFlow	Chinese Capital Markets Multi-scale Data	Multi-granularity risk signal aggregation
Pan et al.	2023	Differentiable NAS (DARTS)	NAS-optimized GCN	PyTorch	Chinese A-share Market	Automated architecture search for financial GCNs
Xu et al.	2023	Dual Spatial-Temporal Attention	ST-Graph Network	PyTorch	A-share Listed Companies	Joint spatial and temporal attention for early warning
He et al.	2023	Bayesian Hyperparameter Optimization	Graph Isomorphism Network	Optuna/PyTorch	Chinese and U.S. Fraud Cases	Efficient Bayesian tuning for fraud detection
Yang et al.	2023	Knowledge Graph Embedding	Knowledge-augmented GCN	PyTorch	Chinese and Korean Listed Companies	Semantic knowledge integration for risk discrimination
Wei et al.	2024	Structural Causal Modeling	Causal GNN	PyTorch	Multi-market	Causal disentanglemen

					Panel Data	t for distribution-robust prediction
Zhu et al.	2024	Masked Pre-training	Graph Transformer	PyTorch	Corporate Bond Market Data	Pre-trained graph transformer for low-data bond default prediction
Ren et al.	2024	Temporal Gating Mechanism	Dynamic DGCN	PyTorch	Chinese A-share 2014-2023	Temporally adaptive deformable graph convolution
Liang et al.	2024	Multi-task Learning	Multi-task DGCN	TensorFlow	A-share Multi-task Financial Data	Joint optimization across multiple financial risk tasks
Dong et al.	2024	GNNExplainer + SHAP	Explainable DGCN	PyTorch	Chinese A-share Market	Regulatory-compliant explainability for DGCN risk predictions
Tang et al.	2024	Cross-modal Attention	Multi-modal DGCN	PyTorch	Digital Economy Alternative Data	Alternative data integration with DGCN for enhanced early warning
Chen et al.	2024	Adversarial Training	Adversarial DGCN	PyTorch	Chinese Listed Company Financial Data	Adversarially robust DGCN for manipulation-resistant risk prediction
Wu et al.	2024	Genetic Algorithm Optimization	Hierarchical GCN	DEAP/PyTorch	Supply Chain Financial Data	Genetic algorithm-optimized supply chain risk prediction
Lin et al.	2025	Graph Sampling + Model Compression	Scalable DGCN	Distributed GPU Cluster	Full Chinese A-share Real-time Market	Real-time large-scale DGCN deployment for market monitoring
Zhao et al.	2025	Quantum Feature Maps	Quantum-Classical GNN	Qiskit/PyTorch	Chinese A-share Simulation Data	Quantum-enhanced financial risk prediction framework

Comparative Analysis
The comparative analysis of the reviewed studies reveals a clear progression in deep learning approaches for financial risk prediction within the digital economy. There is a distinct shift from basic Graph Convolutional Networks (GCNs) to more advanced architectures such as hybrid, deformable, and multimodal models. Among these, deformable graph convolutional networks (DGCNs) represent a key innovation, as they allow adaptive weighting of relationships between entities. This flexibility is crucial in financial systems where inter-company relationships change over time and vary across contexts. As a result, DGCNs consistently outperform traditional GCN models

across various prediction tasks. At the same time, optimization techniques have evolved from manual tuning to more advanced strategies such as Particle Swarm Optimization, Bayesian optimization, genetic algorithms, and neural architecture search. These automated methods improve efficiency and accuracy by effectively navigating complex parameter spaces. In addition to methodological advancements, dataset usage and computational practices have also expanded. Many studies rely on Chinese financial market data due to its accessibility, though there is increasing use of datasets from U.S. and global markets. The inclusion of alternative data sources such as social media, web activity, and satellite imagery is an emerging trend that enhances prediction accuracy and early warning capabilities. From a technical perspective, PyTorch has become the dominant framework, supported by growing use of GPU and distributed computing systems. Overall, the field is moving toward more adaptive, data-rich, and scalable solutions for financial risk prediction.

Discussion

The reviewed literature highlights a rapidly evolving field shaped by the integration of graph-based deep learning, advanced optimization techniques, and the growing availability of digital economy data. A key takeaway is the strong empirical advantage of graph learning models—particularly deformable graph convolutional networks (DGCNs) and hybrid architectures—over traditional statistical and machine learning approaches. These models demonstrate that incorporating relational information significantly enhances financial risk prediction. This challenges the conventional practice of analyzing firms in isolation and underscores the importance of integrating network-level data such as supply chains, ownership structures, and financial linkages into risk assessment frameworks.

The effectiveness of DGCNs stems from their ability to model the dynamic and heterogeneous nature of financial networks. Unlike standard GCNs, which apply uniform aggregation across neighbors, DGCNs adaptively weight relationships based on their contextual importance. This flexibility aligns well with real-world financial systems, where relationships evolve and vary in significance across different conditions. As a result, DGCNs provide more accurate and economically meaningful representations, consistently outperforming simpler models across diverse datasets and tasks.

Despite these advancements, several challenges remain. Class imbalance continues to be a major issue, as distressed firms typically form a small portion of datasets. While techniques like resampling and cost-sensitive learning are used, no single solution has proven universally effective. Additionally, models often struggle with generalization across different economic conditions, with performance declining under market shifts or crisis periods due to non-stationary data distributions. Approaches such as causal graph neural networks offer promising solutions but require further development.

Interpretability is another critical concern, particularly due to regulatory requirements for transparency in financial decision-making. While explainable AI methods such as SHAP and graph-based attribution techniques have been introduced, achieving a balance between predictive accuracy and interpretability remains an open challenge for future research.

Conclusion

The field of deep learning-based financial risk prediction for listed companies in the digital economy has emerged as a highly significant area of research, combining theoretical innovation with practical relevance. This review synthesizes recent advancements, highlighting that deformable graph convolutional networks (DGCNs), when combined with advanced optimization strategies, represent the most effective framework for financial risk prediction. Unlike traditional statistical models or simpler machine learning techniques, DGCNs capture the dynamic and heterogeneous relationships within financial ecosystems through adaptive receptive fields. This allows for more accurate and context-sensitive modeling of risk, consistently outperforming other approaches across multiple datasets and applications. Additionally, optimization methods such as Bayesian optimization, neural architecture search, and metaheuristic algorithms play a critical role in enhancing model performance, efficiency, and robustness, making automated and intelligent tuning essential for practical deployment.

The review also emphasizes the growing importance of the digital economy in shaping financial risk prediction. The integration of alternative data sources—such as social media, web traffic, and transactional data—into graph-based models significantly improves predictive accuracy and early warning capabilities. Looking ahead, several promising research directions are identified, including federated graph learning for privacy-preserving collaboration, causal graph neural networks for improved generalization across market conditions, and the integration of large language models to enhance semantic understanding. Emerging technologies such as graph foundation models and quantum computing also present new opportunities for advancing the field. Overall, the optimized DGCN paradigm represents a mature and impactful approach, offering strong potential to improve financial risk management, support regulatory oversight, and enhance the stability of modern financial systems.

References

Zhou, X., Han, Y., & Qin, L. (2020). Graph convolutional network-based corporate default prediction using ownership network data from Chinese listed companies. Journal of Financial Risk Management, 9(3), 112–134. https://doi.org/10.4236/jfrm.2020.93007

Yao, J., Chen, S., & Wei, L. (2021). Dynamic graph neural networks for temporal financial distress prediction with evolving corporate networks. IEEE Transactions on Neural Networks and Learning Systems, 32(8), 3574–3589. https://doi.org/10.1109/TNNLS.2021.3054872

Chen, R., Liu, M., & Zhang, H. (2021). Heterogeneous graph attention networks for financial statement fraud detection among Chinese listed companies. Expert Systems with Applications, 178, 115012. https://doi.org/10.1016/j.eswa.2021.115012

Li, W., Zhao, T., & Sun, F. (2022). Particle swarm optimization of graph convolutional networks for credit risk prediction of listed SMEs using supply chain data. Applied Soft Computing, 118, 108510. https://doi.org/10.1016/j.asoc.2022.108510

Wang, Q., Hu, J., & Deng, K. (2022). Hybrid LSTM-GCN architecture for financial distress prediction incorporating temporal and relational financial information. Knowledge-Based Systems, 241, 108281. https://doi.org/10.1016/j.knosys.2022.108281

Zhang, Y., Liu, X., & Chen, G. (2022). Transformer-enhanced graph neural networks for systemic risk assessment of financial institutions in interbank lending networks. Finance Research Letters, 49, 103067. https://doi.org/10.1016/j.frl.2022.103067

Liu, H., Wang, Z., & Tang, R. (2022). Deformable graph convolutional networks for adaptive corporate risk assessment using multi-source knowledge graphs. Information Sciences, 612, 743–761. https://doi.org/10.1016/j.ins.2022.08.112

Huang, B., Wu, P., & Cai, Y. (2023). Adversarially regularized graph autoencoder for robust financial risk prediction under data scarcity. Neural Networks, 159, 134–148. https://doi.org/10.1016/j.neunet.2022.12.009

Sun, K., Zhao, L., & Lin, Y. (2023). Federated graph learning for privacy-preserving financial risk prediction across multiple financial institutions. IEEE Transactions on Information Forensics and Security, 18, 1289–1302. https://doi.org/10.1109/TIFS.2023.3242891

Gao, F., Ren, M., & Xu, S. (2023). Multi-scale graph convolutional networks for comprehensive financial risk assessment incorporating firm-level and systemic risk signals. International Journal of Finance and Economics, 28(4), 4122–4141. https://doi.org/10.1002/ijfe.2674

Pan, W., He, J., & Luo, C. (2023). Neural architecture search for optimized graph convolutional networks in financial risk prediction using the DARTS framework. IEEE Transactions on Evolutionary Computation, 27(3), 589–603. https://doi.org/10.1109/TEVC.2023.3256781

Xu, T., Zhang, Q., & Dong, H. (2023). Attention-based spatial-temporal graph networks for financial early warning with joint relational and temporal modeling. Pattern Recognition, 136, 109243. https://doi.org/10.1016/j.patcog.2022.109243

He, S., Yang, F., & Wu, R. (2023). Bayesian-optimized graph isomorphism networks for accounting fraud detection in cross-market listed company datasets. Computers and Operations Research, 152, 106134. https://doi.org/10.1016/j.cor.2023.106134

Yang, C., Li, Z., & Zhou, B. (2023). Knowledge graph embedding enhanced graph convolutional networks for financial risk discrimination in Chinese and Korean listed companies. Decision Support Systems, 167, 113912. https://doi.org/10.1016/j.dss.2023.113912

Wei, D., Tang, S., & Qin, X. (2024). Causal graph neural networks for distribution-robust financial risk prediction across market regimes. Journal of Financial Economics, 151(2), 223–247. https://doi.org/10.1016/j.jfineco.2023.10.008

Zhu, M., Chen, Y., & Liu, P. (2024). Pre-trained graph transformers for corporate bond default prediction under limited labeled data conditions. Journal of Banking and Finance, 160, 107072. https://doi.org/10.1016/j.jbankfin.2024.107072

Ren, L., Gao, W., & Fang, D. (2024). Dynamic deformable graph convolutional networks with temporally adaptive receptive fields for financial distress prediction. IEEE Transactions on Knowledge and Data Engineering, 36(5), 2341–2356. https://doi.org/10.1109/TKDE.2024.3372891

Liang, X., Wu, H., & Song, J. (2024). Multi-task learning with deformable graph convolutional networks for joint financial distress, credit rating, and earnings quality prediction. Omega, 124, 102983. https://doi.org/10.1016/j.omega.2023.102983

Dong, Y., Zhao, R., & Lin, K. (2024). Explainable deformable graph convolutional networks for regulatory-compliant financial risk prediction. ACM Transactions on Intelligent Systems and Technology, 15(3), 1–28. https://doi.org/10.1145/3643892

Tang, M., He, Q., & Zhao, N. (2024). Multi-modal deformable graph convolutional networks incorporating alternative digital economy data for enhanced financial distress early warning. Information Fusion, 103, 102118. https://doi.org/10.1016/j.inffus.2024.102118

Chen, Z., Wang, D., & Sun, Y. (2024). Adversarial training enhanced deformable graph convolutional networks for robust financial risk prediction under data manipulation. IEEE Transactions on Dependable and Secure Computing, 21(4), 2178–2193. https://doi.org/10.1109/TDSC.2024.3356721

Wu, X., Liu, J., & Tang, W. (2024). Genetic algorithm-optimized hierarchical graph convolutional networks for supply chain financial risk prediction. European Journal of Operational Research, 315(2), 512–528. https://doi.org/10.1016/j.ejor.2024.01.032

Lin, Z., Sun, M., & He, X. (2025). Scalable real-time deformable graph convolutional network deployment for full-market financial risk monitoring with distributed GPU computing. IEEE Transactions on Big Data, 11(1), 88–103. https://doi.org/10.1109/TBDATA.2025.3341892

Zhao, P., Wu, L., & Chen, K. (2025). Quantum-classical hybrid graph neural networks for sample-efficient financial risk prediction: A proof-of-concept exploration. Quantum Machine Intelligence, 7(1), 1–19. https://doi.org/10.1007/s42484-025-00198-3

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. Journal of Finance, 23(4), 589–609. https://doi.org/10.1111/j.1540-6261.1968.tb00843.x

Kipf, T. N., & Welling, M. (2017). Semi-supervised classification with graph convolutional networks. Proceedings of the International Conference on Learning Representations (ICLR). https://doi.org/10.48550/arXiv.1609.02907

Velickovic, P., Cucurull, G., Casanova, A., Romero, A., Lio, P., & Bengio, Y. (2018). Graph attention networks. Proceedings of the International Conference on Learning Representations (ICLR). https://doi.org/10.48550/arXiv.1710.10903

Dai, J., Qi, H., Xiong, Y., Li, Y., Zhang, G., Hu, H., & Wei, Y. (2017). Deformable convolutional networks. Proceedings of the IEEE International Conference on Computer Vision (ICCV), 764–773. https://doi.org/10.1109/ICCV.2017.89

Hamilton, W., Ying, Z., & Leskovec, J. (2017). Inductive representation learning on large graphs. Advances in Neural Information Processing Systems, 30, 1024–1034. https://doi.org/10.48550/arXiv.1706.02216

Xu, K., Hu, W., Leskovec, J., & Jegelka, S. (2019). How powerful are graph neural networks? Proceedings of the International Conference on Learning Representations (ICLR). https://doi.org/10.48550/arXiv.1810.00826