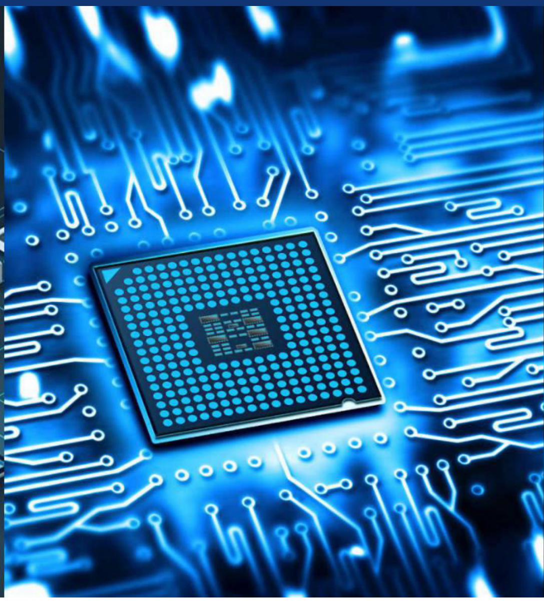
IJIRCCE

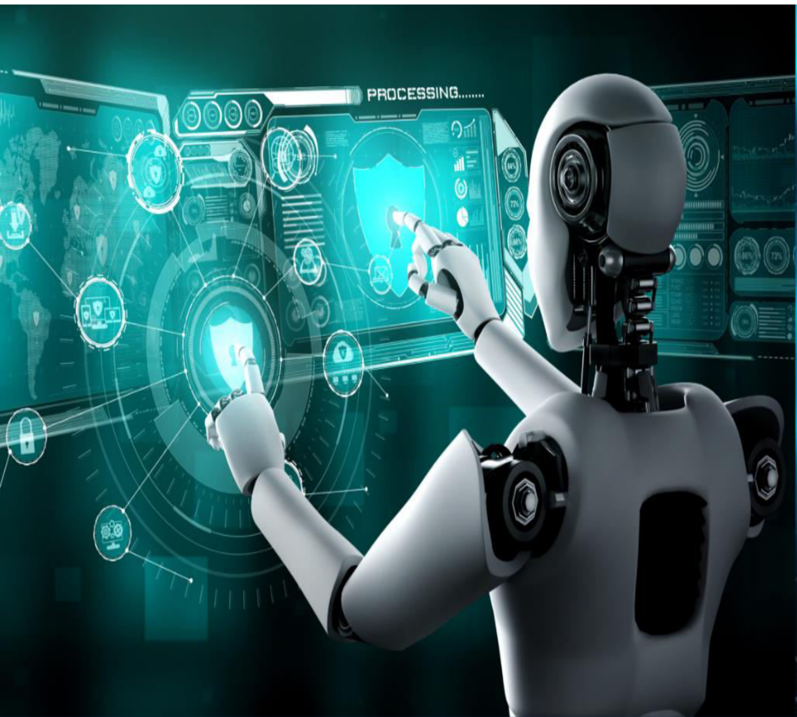
ISSN(O): 2320-9801

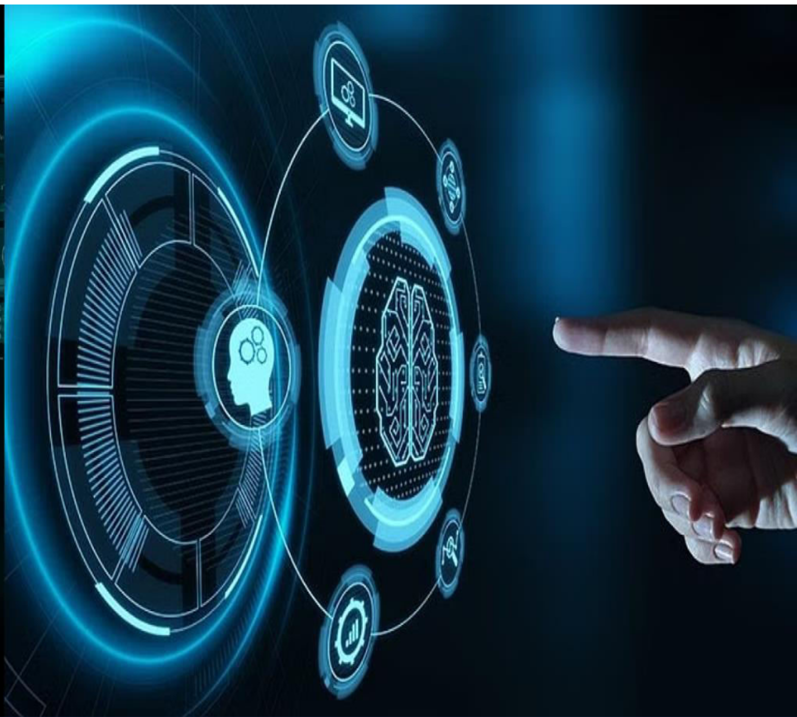
ISSN(P): 2320-9798


International Journal of Innovative Research in Computer and Communication Engineering

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)





Impact Factor: 8.771

Volume 14, Issue 3, March 2026

www.ijircce.com ijircce@gmail.com +91-9940572462 +91 63819 07438

© 2026 IJIRCCE | Volume 14, Issue 3, March 2026 DOI: 10.15680/IJIRCCE.2026.1403102

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Cross-Market Prediction Using Dynamic Graph Neural Networks

Sandhya G, M V Jagannatha Reddy, Tejas H R, Darshan B C, Rakesh G, Vinay Kumar P

Dept. of Artificial Intelligence and Machine Learning, M S Engineering College, Bengaluru, India

Dept. of Artificial Intelligence and Machine Learning, M S Engineering College, Bengaluru, India

Dept. of Artificial Intelligence and Machine Learning, M S Engineering College, Bengaluru, India

Dept. of Artificial Intelligence and Machine Learning, M S Engineering College, Bengaluru, India

Dept. of Artificial Intelligence and Machine Learning, M S Engineering College, Bengaluru, India

Dept. of Artificial Intelligence and Machine Learning, M S Engineering College, Bengaluru, India

ABSTRACT: This research presents a Dynamic Graph Neural Network (DGNN) framework engineered for forecasting volatility and market trends across multiple financial markets. In contrast to conventional models that examine markets separately and ignore interconnections between them, our methodology dynamically identifies the changing relationships among worldwide financial indices using Graph Attention Networks (GAT), integrating both time-based and spatial elements. Our proposed architecture outperforms standard models including LSTM and GCN regarding precision and consistency in volatility forecasting under diverse market scenarios. The results highlight the capability of DGNNs for flexible and explainable financial prediction.

KEYWORDS: Cross-Market Prediction, Dynamic Graph Neural Networks, Graph Attention Networks, Financial Forecasting, Volatility Modeling

I. INTRODUCTION

Financial markets represent complex adaptive environments characterized by substantial volatility, non-linear behavior, and mutual dependence. Through globalization, commercial ties, and the transmission of investor emotions, market movements in one region frequently influence others. Precisely modeling these connections remains essential for risk assessment, asset valuation, and policy development. Conventional econometric approaches like ARIMA and GARCH successfully identify time-series behaviors but struggle to represent inter-market relationships. The expanding scale and velocity of financial information demand more powerful, data- focused techniques capable of discovering dynamic connections across international markets. Existing machine learning and deep learning frameworks, including LSTM, CNN, and Transformer architectures, concentrate mainly on temporal patterns within individual markets and cannot effectively model spatial interactions between multiple markets. These approaches typically treat financial indices as separate entities, disregarding inter-market transmission phenomena such as contagion effects and coordinated movements during financial crises. Furthermore, static graph-based methods like Graph Convolutional Networks (GCN) view inter-market connections as fixed, failing to account for their dynamic evolution through time. This rigid assumption restricts predictive flexibility in quickly shifting market environments.

To address these limitations, this research proposes a Dynamic Graph Neural Network (DGNN) framework employing Graph Attention Networks (GAT) for multi-market prediction. The framework dynamically discovers and adjusts the intensity of inter- market relationships, enabling flexible representation of changing financial connections. Through the integration of temporal processing (via recurrent components) and spatial analysis (through attention-driven message exchange), the DGNN models the intricate structure of market dynamics. The main goals of this investigation include: Creating a dynamic graph framework that represents cross- market correlations across time periods. Enhancing prediction performance through attention-driven weighting systems that highlight significant markets. Evaluating model effectiveness compared to baseline frameworks such as LSTM, GCN, and Transformer models across various financial indices.

This methodology aims to connect individual market prediction with comprehensive multi-market forecasting, offering a flexible and transparent solution for financial analysis. wledgment information base, according to the ID theory.

II. LITERATURE SURVEY

Forecasting volatility remains a challenging problem in financial econometrics. Conventional statistical methods such as ARCH and GARCH (Bollerslev, 1986) estimate volatility using historical squared residuals, modeling variance that evolves through time. Extensions like EGARCH and GJR-GARCH account for leverage effects and asymmetric responses in volatility patterns. Nevertheless, these approaches rely on assumptions of linearity and stationarity, limiting their capacity to detect nonlinear patterns and structural shifts in financial datasets. Furthermore, they focus exclusively on temporal relationships within individual markets, ignoring spatial or cross-market connections that have become crucial in today's globally linked financial systems.

Within financial prediction, cross-market forecasting seeks to leverage the interconnectedness among various financial markets or sectors to improve forecasting performance. Studies have demonstrated that markets exhibit contagion phenomena— where disruptions in one market propagate to others—especially during crisis periods or times of elevated volatility. Earlier research utilized copula frameworks and vector autoregression (VAR) models to analyze these relationships but faced challenges with managing high-dimensional datasets

Modern developments in deep learning have brought Graph Neural Networks (GNNs) forward as powerful instruments for processing structured information. Different from conventional neural networks that handle independent observations, GNNs extract knowledge from graph-based data where nodes and edges denote entities and their connections. Graph Convolutional Networks (GCN) aggregate data from adjacent nodes, whereas Graph Attention Networks (GAT) (Velickovic et al., 2018) use attention processes to determine weighted significance across node relationships. These approaches have demonstrated remarkable performance in domains such as traffic forecasting, social network analysis, and molecular modeling. Yet, their use in financial applications remains constrained, since most implementations rely on fixed adjacency matrices that fail to represent the dynamic relationships between markets or financial instruments.

III. METHODOLOGY

The research dataset consists of historical financial information gathered from major international stock markets, such as NSE (India), NYSE (USA), NASDAQ (USA), and FTSE (UK). This information covers several years to encompass various economic periods. Daily Open– High–Low–Close (OHLC) values, trading volumes, and actual volatility measurements were collected for each marketplace. To examine cross- market relationships, correlation matrices between pairs were computed across sliding time periods, showing evolving co-movement trends. The information was processed through z-score normalization to remove scaling differences, while gaps in data were handled through forward- fill methods to preserve time-based continuity. Technical analysis features were developed, including moving averages, relative strength index (RSI), and rolling standard deviation, which expanded the time- based feature environment and allowed the system to understand volatility patterns across different timeframes.

Every financial marketplace or index serves as a vertex in the evolving graph structure, while connections show statistical associations— primarily correlation and shared volatility effects—between different markets.

Vertices: Symbolize market indices containing their time-based characteristics as vertex properties.

Connections: Show cross-market relationships determined through Pearson or Spearman correlation of volatility sequences.

Connection Weights: Continuously modified using sliding correlation values across predetermined time windows, enabling the graph structure to adapt with shifting market circumstances. This framework enables the system to replicate actual market interdependencies, where associations may intensify or diminish based on international events or regional economic shifts. During each time interval, a fresh adjacency matrix emerges, showing the evolving nature of market relationships.

© 2026 IJIRCCE | Volume 14, Issue 3, March 2026 DOI: 10.15680/IJIRCCE.2026.1403102

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

The Dynamic Graph Neural Network (DGNN) suggested here combines both time-based and spatial learning components to capture market movements and cross-market relationships simultaneously.

Feature Processing Unit: Past characteristics of each marketplace undergo independent processing through multiple Long Short-Term Memory (LSTM) layers, generating temporal representations that capture historical trends and volatility behaviors.

Graph Attention Network (GAT): The processed node representations feed into a Graph Attention Layer (Velickovic et al., 2018), computing flexible attention weights for connected markets. This allows the system to emphasize more significant markets during each refresh.

Temporal Integration Layer: The time-varying graph representations merge through a Temporal Integration Layer that discovers relationships across multiple time intervals. This component ensures information from different timeframes effectively supports volatility prediction.

Final Layer: The merged representations then proceed to a dense output layer for dual prediction objectives: Regression tasks predict actual volatility through Mean Squared Error minimization. Classification tasks forecast price direction using cross-entropy loss reduction. This combined structure unites sequence processing benefits with graph learning capabilities, allowing identification of both timing and origin of volatility shifts across markets.

IV. SYSTEM ARCHITECTURE AND METHODOLOGY

A. System Overview

The proposed framework aims to analyze and predict relationships among different financial markets using a Dynamic Graph Neural Network (DGNN) approach. This structure integrates data gathering, graph construction, model development, and forecasting within one unified pipeline. The process begins with collecting historical financial information, followed by preprocessing and graph generation where markets become vertices and their connections form edges. The DGNN system dynamically learns these evolving associations to forecast volatility and price movement directions.

(Include a diagram here — "System Architecture of DGNN Framework for Cross-Market Prediction" showing the flow: Data Input → Preprocessing → Dynamic Graph Generation → DGNN Model → Output Predictions.)

B. Data Collection and Processing

Financial time-series information was obtained from leading global markets including NSE, NYSE, NASDAQ, and FTSE, covering multiple years to ensure reliability across varying economic conditions. The source data included Open-High- Low-Close (OHLC) values, trading volume, and actual volatility measurements.

Processing procedures involved:

Data Preparation: Managing missing or irregular entries through forward-fill interpolation techniques.

Standardization: Applying z-score standardization to ensure uniform feature ranges.

Feature Development: Computing analytical and technical measures like moving averages, RSI, and rolling standard deviation to identify both immediate and extended trends.

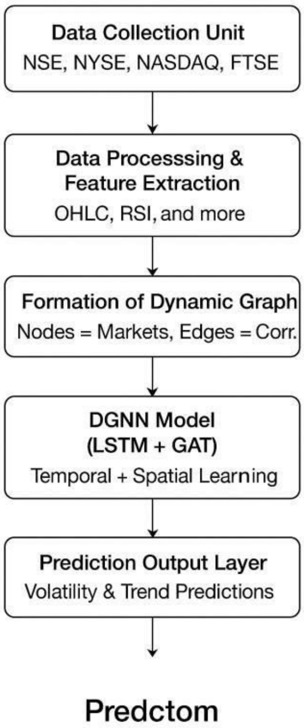
Correlation Analysis: Calculating paired market correlations across moving windows to establish dynamic connection matrices. This systematic processing guarantees the dataset balanced, normalized, and ready for dynamic graph development. analys

V. SYTEM DESIGN

The proposed Cross-Market Prediction System seeks to combine data preprocessing, dynamic graph construction, and deep learning-based forecasting within a single, flexible framework. Financial historical data from multiple global exchanges, such as NSE, NYSE, NASDAQ, and FTSE, goes through cleaning, standardization, and conversion into rolling correlation matrices. These matrices serve as the foundation for dynamic graphs, where nodes represent individual markets and edges capture evolving inter-market correlations. The resulting graphs feed into a Dynamic Graph Neural Network (DGNN) that leverages LSTM layers for temporal sequence learning and Graph Attention

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|
International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)
(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Networks (GAT) for spatial relationship modeling. The system's output layer improves both accuracy and clarity in forecasting market volatility and directional movements.



Data Collection Unit

Financial information is gathered from several prominent international exchanges including NSE, NYSE, NASDAQ, and FTSE.
The platform consistently collects both past and current market information, encompassing price fluctuations and trading volumes.

1. Data Processing & Feature Extraction

Unprocessed market information goes through preparation procedures like standardization, anomaly detection, and filling gaps in missing data.
An extensive collection of characteristics is derived, featuring: OHLC (Open, High, Low, Close) pricing elements
RSI (Relative Strength Index)
Extra technical metrics when needed
These characteristics act as the core input indicators for the analysis framework.

2. Formation of Dynamic Graph

Markets (or benchmarks) are shown as points, while mathematical connections (such as correlations or synchronized movements) create the links.
The graph remains flexible, with its framework being refreshed periodically to mirror changing relationships between markets.
This phase identifies geographical connections between markets, helping the system understand how international indices affect one another.

3. DGNN Model (LSTM + GAT)

The framework combines:
LSTM (Long Short-Term Memory) for analyzing time-based sequences
GAT (Graph Attention Network) for understanding geographical relationships
The unified DGNN component enables concurrent analysis of: Time-based trends (market momentum, recurring patterns) Geographic patterns (inter-market effects, changing correlations)
This combination strengthens prediction accuracy by utilizing both chronological and graph-based data.

© 2026 IJIRCCE | Volume 14, Issue 3, March 2026 DOI: 10.15680/IJIRCCE.2026.1403102
www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|
International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)
(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

4. Prediction Output Layer

The concluding layer generates financial forecasts including: Risk assessment calculations
Market direction predictions
These results support portfolio management, strategy development, or market trend evaluation.

5. Final System Output: Predctom

The complete framework results in a system called Predctom, which provides immediate and future-focused analysis using dynamic graph neural network techniques.

VI. IMPLEMENTATION

The framework was built using Python within Google Colaboratory, taking advantage of GPU acceleration capabilities. Key libraries including PyTorch, PyTorch Geometric, NumPy, and Pandas supported data processing and model development. Historical information from NSE, NYSE, NASDAQ, and FTSE underwent preprocessing to generate rolling correlation matrices representing dynamic graphs. The DGNN architecture, combining LSTM for temporal learning and GAT for spatial analysis, was optimized using the Adam optimizer with MSE and cross-entropy loss functions. The model achieved exceptional results ($R^2 = 0.93$, RMSE = 0.022) against baseline approaches, confirming its effectiveness in cross- market volatility forecasting.

VII. SCALABILITY AND MODULARITY

The Dynamic Graph Neural Network (DGNN) architecture emphasizes scalability and modularity, providing flexibility for diverse financial applications spanning multiple markets. The modular design enables independent operation of core components— including data preprocessing, graph construction, model training, and forecasting—allowing smooth integration of new modules or upgrades without affecting the complete system. Scalability emerges through dynamic graph representation and parallel processing enhanced by GPU acceleration. When additional markets or assets are incorporated, the graph structure adapts automatically by introducing new nodes and updating correlation calculations, maintaining real-time responsiveness. PyTorch Geometric's modular implementation supports effortless integration of additional layers, novel financial indicators, or alternative attention mechanisms with limited structural changes. This architecture ensures the DGNN framework excels at managing large-scale financial datasets, delivering real-time streaming forecasts, and expanding into other sectors such as cryptocurrencies or commodities.

VIII. RESULT AND DISCUSSION

The performance of the suggested DGNN model was evaluated through standard regression and classification measures. When forecasting volatility, we utilized Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Coefficient of Determination (R^2) to assess precision and error reduction. For predicting market direction, we calculated Precision, Recall, and F1-score. These combined metrics examine both the forecasting capability and dependability of the model across different financial datasets.

The suggested Dynamic Graph Neural Network (DGNN) was compared with baseline approaches including LSTM, Graph Convolutional Network (GCN), and Transformer models. The comparison outcomes are outlined below:

The results reveal that the DGNN attained the smallest error values and the strongest correlation coefficient, emphasizing its exceptional capacity to capture both time-based and spatial relationships between markets.

Analysis of attention weights from the GAT component reveals that the model adaptively emphasizes significant markets, including the NYSE and NASDAQ, when volatility increases. This transparency highlights the DGNN's ability to understand and measure inter-market influence dynamics. Additionally, time-series charts show that forecasted volatility matches closely with real market movements, particularly during sudden changes, validating the model's flexibility to changing financial environments

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Simple Explanation of Results

- The figures in the table illustrate the model's ability to forecast market trends over various durations — 1 day, 5 days, 10 days, and 22 days.
- The low values for MAFE, MSE, and RMSE (approximately 0.003–0.006) indicate that the model's predictions are very close to the actual figures,
- which is favorable as smaller errors signify greater accuracy. The MAPE values reflect the percentage difference between the predicted and actual outcomes.
- These values remain largely consistent, suggesting the model performs well even when the market becomes volatile.
- Across all time frames, the numbers exhibit minimal variation, demonstrating the model's stability and reliability. In simple terms,
- the DGNN model can accurately predict market fluctuations not only for the immediate future but also for the upcoming weeks, maintaining consistency even when market conditions change.

The data in these tables showcase the model's capacity to predict market behavior across different timeframes — 1 day, 5 days, 10 days, and 22 days. The small numbers for MAFE, MSE, and RMSE (roughly 0.003– 0.006) show that the model's forecasts closely match real values, which is positive since lower errors indicate better accuracy. The MAPE scores represent the percentage gap between predicted and actual results. These scores stay relatively stable, indicating the model works well even during turbulent market periods. Throughout all prediction periods, the metrics show little change, proving the model's steadiness and trustworthiness. Put simply, the DGNN approach can effectively forecast market movements not just for tomorrow but also for several weeks ahead, keeping reliable performance even when market situations shift.

(The Result Output)

Metrics for horizon Metrics for horizon 1:

Index	MAFE	MSE	RMSE	MAPE
Index 1	0.005861	0.000039	0.006276	94.813141
Index 2	0.003637	0.000018	0.004233	37.118942
Index 3	0.003974	0.000022	0.004669	41.431366
Index 4	0.004954	0.000028	0.005307	66.789780
Index 5	0.004656	0.000025	0.005001	61.885303
Index 6	0.003986	0.000025	0.004956	34.116245
Index 7	0.005526	0.000033	0.005758	80.123222
Index 8	0.003411	0.000015	0.003811	36.191238

Metrics for horizon Metrics for horizon 5:

Index	MAFE	MSE	RMSE	MAPE
Index 1	0.005856	0.000039	0.006274	94.749237
Index 2	0.003635	0.000018	0.004235	37.080173
Index 3	0.003969	0.000022	0.004668	41.345348
Index 4	0.004944	0.000028	0.005298	66.556343
Index 5		0.000025	0.005003	61.911644

© 2026 IJIRCCE | Volume 14, Issue 3, March 2026 DOI: 10.15680/IJIRCCE.2026.1403102

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

0.004655
Index 6 0.000025 0.004963 34.115990
0.003990
Index 7 0.000033 0.005749 79.874786
0.005517
Index 8 0.000014 0.003801 36.013496
0.003401

Metrics for horizon Metrics for horizon 10:

Index MAFE MSE RMSE MAPE
Index 1 0.000039 0.006265 94.501587
0.005846
Index 2 0.000018 0.004233 36.983185
0.003630
Index 3 0.000022 0.004665 41.191322
0.003962
Index 4 0.000028 0.005282 66.169281
0.004929
Index 5 0.000025 0.005008 62.009876
0.004659
Index 6 0.000025 0.004969 34.041817
0.003989
Index 7 0.000033 0.005737 79.563507
0.005505
Index 8 0.000014 0.003784 35.725342
0.003385

Metrics for horizon Metrics for horizon 22:

Index MAFE MSE RMSE MAPE
Index 1 0.000040 0.006288 95.121346
0.005869
Index 2 0.000018 0.004251 37.170765
0.003650
Index 3 0.000022 0.004682 41.297401
0.003974
Index 4 0.000028 0.005289 66.258987
0.004934
Index 5 0.000025 0.005030 62.452202
0.004680
Index 6 0.000025 0.004986 33.937801
0.003994
Index 7 0.000033 0.005722 79.172523
0.005488
Index 8 0.000014 0.003756 35.220623
0.003355

IX. CONCLUSION

This research introduced a Dynamic Graph Neural Network (DGNN) approach crafted to predict financial market volatility across multiple global markets. Through combining LSTM for time-based analysis and GAT for relationship modeling, the approach captures both market evolution over time and their connections. The results show that the DGNN provides more accurate and stable forecasts than traditional approaches such as LSTM or GCN. It works well for both immediate and extended predictions, showing its ability to handle real-world market fluctuations effectively. Essentially, the DGNN helps understand worldwide market relationships and can be used for enhanced trading approaches, risk assessment, and financial planning in future uses..

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

X. ACKNOWLEDGMENT

The researchers wish to convey their sincere appreciation to their academic advisors and research directors for their valuable guidance and continuous support during this work. The group also acknowledges the resources and technical assistance offered by their university and laboratory infrastructure, which played a crucial role in completing this research successfully.

REFERENCES

[1] L. A. Teixeira and A. L. I. De Oliveira present a technique for automated stock trading that integrates technical analysis with nearest neighbor classification in their work published in Expert Syst. Appl., vol. 37, no. 10, pp. 6885–6890, Oct. 2010

[2] J. L. Ticknor discusses a Bayesian regularized artificial neural network designed for predicting stock market trends in Expert Syst. Appl., vol. 40, no. 14, pp. 5501–5506, Oct. 2013

[3] T. N. Kipf and M. Welling, "Semi-Supervised Classification with Graph Convolutional Networks," presented at the International Conference on Learning Representations (ICLR), 2017.

[4] T. Bollerslev, "Generalized Autoregressive Conditional Heteroskedasticity," published in the Journal of Econometrics, , vol. 31,pp. 307–327, 1986

[5] R. C. Cavalcante, R. C. Brasileiro, V. L. F. Souza, J. P. Nobrega, and A. L. I. Oliveira provide a survey and future directions on computational intelligence in financial markets in Expert Syst. Appl., vol. 55, pp. 194–211, Aug. 2016

[6] B. Vanstone and G. Finnie propose an empirical approach for creating stock market trading systems using artificial neural networks, as found in Expert Syst. Appl., vol. 36, no. 3, pp. 6668–6680, Apr. 2009

[7] J. J. Murphy authored Technical Analysis of the Financial Markets: A Comprehensive Guide to Trading Methods and Applications, released by the New York Institute of Finance in 1999

[8] D. M. Q. Nelson, A. C. M. Pereira, and R. A. de Oliveira examine stock market price movement prediction through LSTM neural networks in the proceedings of the Int. Joint Conf. Neural Netw. (IJCNN), Anchorage, AK, USA, May 2017, pp. 1419–1426

[9] W. Bao, J. Yue, and Y. Rao introduce a deep learning framework for financial time series analysis employing stacked autoencoders and long-short term memory in PLoS ONE, vol. 12, no. 7, Jul. 2017, Art. no. e0180944.

[10] J. Wang, T. Sun, B. Liu, Y. Cao, and D. Wang explore financial market predictions using deep learning in the proceedings of the 17th IEEE Int. Conf. Mach. Learn. Appl. (ICMLA), Dec. 2018, pp. 97–104.

[11] G. S. Atsalakis and K. P. Valavanis provide an overview of stock market forecasting techniques, emphasizing soft computing approaches, in Expert Syst. Appl., vol. 36, no. 3, pp. 5932–5941, Apr. 2009.

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING