Stock Market Telepathy: Graph Neural Networks Predicting the Secret Conversations between MINT and G7 Countries

Nurbanu Bursa[a,b]

[a] *Hacettepe University, Department of Statistics, Beytepe, 06800, Ankara, Türkiye*
[b] *Boise State University, Biomedical Research Institute, Boise, 83725, Idaho, USA*

Abstract

Emerging economies, particularly the MINT countries (Mexico, Indonesia, Nigeria, and Türkiye), are gaining influence in global stock markets, although they remain susceptible to the economic conditions of developed countries like the G7 (Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States). It is crucial to have an informed model of the potential effect of one financial market has on another in order for investors and policymakers to predict stock price movements accurately. To this end, in this study we examine the main stock market indices of G7 and MINT countries from 2012 to 2024, using a recent algorithm, called multivariate time series forecasting with graph neural network (MTGNN). This algorithm makes predictions not only on the temporal dependencies of the stock prices, but it also takes into account the spatial relationships between the countries. Indeed, figuring out these spatial relationships is cast as part of the learning problem in MTGNN. Our results show that MTGNN outperforms traditional methods like AR, VAR-MLP, RNN-GRU, and TCN in forecasting stock prices, achieving higher accuracy. This improved predictive capability is particularly beneficial for emerging markets, which are often less stable and more sensitive to both domestic and global economic conditions.

Keywords: Deep learning, G7 countries, Graph neural networks, MINT countries, Multivariate time series, Stock price prediction
JEL: C45, C53, C55, C82, F47, O50

1. Introduction

In the early 2010s, four countries attracted the attention of economists with their highly promising economies, and a new acronym, MINT: Mexico, Indonesia, Nigeria, and Türkiye, emerged (Durotoye, 2014). When the acronym was first suggested by Jim O'Neill, common characteristics of MINT countries were (i) geographical positions *(Mexico sits next to the USA and belongs to the North American Free Trade Agreement (NAFTA), Indonesia lies at the centre of South East Asia, Türkiye is connected to both the West and East, while Nigeria is on the coast of Africa surrounded by future trading partners)*, (ii) large populations *(primarily under 30)*, (iii) rapid economic growth potential, (iv) a developing middle class, and (v) high levels of entrepreneurship (Boesler, 2013; Newland, 2014; Nagashybayeva, 2020). Within the last decade the economic performance of MINT countries have been mixed, with some facing economic difficulties, including high inflation and political uncertainty that affect the investment climate (Okoroafor, 2024). As further detailed in Zhang et al. (2021); Siddiqui and Kaur (2023), MINT countries as emerging economies may not only have been affected by domestic challenges in this decade, but may also have been influenced by global conjuncture. In particular, the policies advanced economies such as the group of seven countries follows have had a huge impact.

The group of seven developed countries (G7), comprises the world's largest and most advanced economies: Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States. They have a substantial impact on the development of global economic policies and trends. As of 2023, these countries may be characterized by the following properties: they (i) have the largest share of the world's gross domestic product (GDP) *(approximately 30% in 2023, it was more than 43% in the early 2000s)*, (ii) are important players in global trade and investment due to multinational corporations, and (iii) have the most liquid and developed financial market centers that influence global capital flows and market dynamics (Economics, 2024; Nations, 2022; Dyvik, 2024). These properties mean that G7 countries significantly impact emerging economies such as BRICS: Brazil, Russia, India, China, South Africa and MINT by shaping their economic policies, trade relations, and financial markets. The stock markets of emerging economies are often highly sensitive and closely tied to financial and economic developments in the G7 countries because financial markets are interconnected (Fratzscher, 2012; Rey, 2015; Acharya et al., 2020). It is of utmost required that investors and policymakers understand and interpret the links between developed and emerging markets. Our goal in this study is to meet this need using the framework of spatio-temporal graph neural networks (GNN). In particular, we employ a particular spatio-temporal GNN instance, MTGNN, to reveal these connections (Wu et al., 2020) and use them to produce very accurate price predictions for both the MINT and G7 stock markets.

Our study contributes to the current literature in a few important ways. First, this study proposes to view the stock market indices of MINT and G7 countries as an interconnected network, modeled by an underlying graph structure that can be learned from historical data. Second, this study demonstrates how spatio-temporal GNN can be used to effectively capture complex and unknown interdependencies between economic blocks, in terms of their stock market indices. Third, leveraging the graph structure of stock indices and their interconnections, the study shows that prediction accuracy and robustness can be significantly improved over traditional, hybrid, and the more-recent deep-learning approaches.

Accurate stock price forecasting is critical to support decision-making across multiple domains, ensuring better financial outcomes and contributing to the stability and growth of the global economy. The significance of this study can be better appreciated by considering how it can be used to create lucrative portfolios while taking into account the interconnectedness of the stock markets of MINT and G7 countries.

The rest of the paper is organized as follows: Section 2 reviews the existing literature about methods of stock price prediction. Section 3 discusses the data and its properties. Section 4 provides a short review of spatio-temporal GNN methodology, in particular that of MTGNN, and Section 5 presents empirical results. Finally, Section 6 provides the conclusions with directions for future research.

2. Literature review

The stock market plays a vital role in the economy of nations, serving as the primary platform for global capital exchange. Hence, the success of the stock market has a substantial impact on the overall state of the national economy. Investors in the stock market strive to maximize their earnings by analyzing market information. Therefore, people might exploit the financial market using accurate models to forecast the stock price, influenced by macroeconomic elements and numerous other factors (Gao et al., 2020). Traditionally, the efficient market hypothesis also argues that future stock prices can be predicted using historical stock data (Fama, 1970; Shahi et al., 2020). However, predicting stock index prices has long been a difficult task for professionals in the financial industry and related fields, mainly due to the presence of non-linearity, volatility, and noise characteristics. Thus, improving the precision of stock index price prediction and obtaining an accurate prediction is still a much-debated topic (Binkowski et al., 2018). In time, several traditional statistical models have been used to predict stock prices using historical data (Jarrett and Kyper, 2011; Tsai, 2012; Mensi et al., 2014; Sahoo and Charlapally, 2015; Cakra and Trisedya, 2015; Suharsono et al., 2017; Ma et al., 2018; Izzeldin et al., 2019; Tulcanaza Prieto and Lee, 2019; Ning et al., 2019).

In the last 20 years, the rise of computational intelligence has led to the development of advanced models *(machine learning, deep-learning, and hybrid models)* for stock market forecasting. Instead of traditional statistical models that can only consider linear structures like autoregressive integrated moving average (ARIMA), vector autoregressive (VAR), plenty of new techniques such as Bayesian networks, fuzzy neural systems, genetic algorithms, recurrent neural networks (RNN), convolutional neural networks (CNN), and long-short term memory (LSTM) have been suggested by numerous researchers (Cheng et al., 2010; Karazmodeh et al., 2013; Chen and Chen, 2015; Chong et al., 2017; Hiransha et al., 2018; Cao et al., 2020; Nikou et al., 2019; Hargreaves and Leran, 2020; Shahi et al., 2020; Setiani et al., 2021; Pahlawan et al., 2021; Alkhatib et al., 2022; Nasiri and Ebadzadeh, 2023).

In addition to all these, in the last five years, the use of graph neural networks in stock price prediction has gained significant attention. Deng et al. (2019) introduced a knowledge-driven temporal convolutional network (KDTCN) for stock trend prediction and explanation, emphasizing the importance of knowledge-driven events in predicting abrupt changes. Long et al. (2020) integrated deep learning and knowledge graph techniques to predict stock price trends in the Chinese stock exchange market. Sawhney et al. (2020b) introduced the spatio-temporal hypergraph convolution network (STHGCN) for stock movement forecasting, highlighting its applications in quantitative trading and investment decision-making. Furthermore, Sawhney et al. (2020a) proposed a deep attentive learning architecture for stock movement prediction, leveraging financial data, social media, and inter-stock relationships through a graph neural network. Wu et al. (2020) discussed a novel approach to multivariate time series forecasting using graph neural networks (MTGNN). Chen et al. (2021) introduced a graph convolutional feature based convolutional neural network (GC-CNN) model for stock trend prediction, demonstrating superior performance using Chinese stock data. Hou et al. (2021) developed the ST-trader model, a spatio-temporal deep neural network for modeling stock market movement, emphasizing the incorporation of inter-connections between firms to forecast stock prices. Lastly, Sawhney et al. (2021) explored the scale-free nature of stock markets and inter-stock correlations, proposing HyperStockGAT as a model for stock selection based on scale-free graph-based learning. These studies collectively highlight the advancements in utilizing graph neural networks for stock price prediction, emphasizing the importance of incorporating various data sources and methodologies to enhance prediction accuracy and decision-making in financial markets.

Building on Wu et al. (2020), this study for the first time employs a GNN framework-MTGNN, which can automatically extract the dependencies are not known in advance, to MINT and G7 countries' stock market indices. The success of the MTGNN method (i) at capturing complex, non-linear relationships over time between variables by representing them as nodes in a graph, (ii) obtaining accurate predictions Wu et al. (2020); Cui et al. (2021); He et al. (2022); Liu et al. (2022); Jin et al. (2022); Chen and Xie (2022); Chen et al. (2023), and (iii) the thought of the countries in the MINT and G7 economic blocs naturally can be represented as a graph, (iv) the high possibility of these countries involving complex, non-linear economic interactions and (v) these interactions between countries is critical to making accurate predictions caused to prefer the MTGNN over other methods.

3. Data

In the study, the main stock market indices were selected to represent the stock market indices of MINT and G7 countries. As can seen from Table 1, FTSE MIB index for Italy, BIST 100 index for Turkiye, CAC 40 index for France, FTSE 100 index for UK, DAX PERFORMANCE index for Germany, S&P 500 index for USA, S&P/TSX index for Canada, IDX COMPOSITE index for Indonesia, IPC MEXICO index for Mexico, NIKKEI 225 index for Japan, and lastly NSE 30 index for Nigeria were chosen.

To perform data analysis, we used daily closing prices for the indices accessed from https://finance.yahoo.com/ and https://www.investing.com. The data were collected from January 30, 2012 to August 14, 2024. The unavailability of old values of NSE 30 index was effective in the selection of this date range. After gathering data, the BIST 100 index was adjusted before the analysis because it reached 100,000 points on June 13, 2017, and two zeros were removed from the index as of July 27, 2020. For this reason, before July 27, 2020, we divided all values by 100 for BIST 100 index.

When the descriptive statistics in Table 2 evaluated, even all indices ara non-normal, it is noteworthy that the BIST 100 and NSE 30 indices, which belong to MINT countries, are most positively skewed and leptokurtic.

All stock market indices values during that time were drawn in Figure 1 for each country. According to Figure 1, although some dates are different, stock market movements seem generally similar because of the wide range of the y-axis. The decline in all of them, especially during the Covid period, is striking.

In addition to all data summaries, Spearman correlation analysis was also applied to indices to examine their relations between themselves. According to Figure 2, among MINT countries, Nigeria's stock index was found to be least correlated with the other countries' indices, Mexico's index was second least correlated, and Türkiye's and Indonesia's were most related. Nonetheless, because the dataset has time-dependent relationships, to use more appropriate method, dynamic time warping (DTW) was also used besides the Spearman correlation analysis. DTW is a robust approach to determine the distance which can be thought of as similarity measure between two time series, which may vary in time. The primary concept of DTW is to calculate the distance by comparing corresponding items in time series that are similar (Gulzar, 2018). Unlike traditional distance measures, such as Euclidean distance, DTW can handle shifts and distortions in the time axis and calculates a cumulative distance by considering the minimum distance path through the cost matrix (Muller, 2007). Lower DTW distances, generally close to 0 ones, indicate that the two time series are more similar. Thus, we can say according to Figure 3, except for the UK's and Indonesia's indices, most indices were very similar to the other countries' indices during the 12-year span.

4. Methodology

In this section, we provided a brief background on GNN and MTGNN, which serves two purposes: (i) familiarize the reader with how they work to produce predictions and (ii) justify their use for price prediction of time series data. Afterward, classical, hybrid, and deep-learning methods contributing as baseline methods to compare MTGNN results are presented.

4.1. Graph neural networks

A graph is a tuple consisting of a set of nodes or vertices, where pairs of nodes are connected by edges or links. This data structure is used to describe the relationships between different entities. Many real-world objects may naturally be described by constructing appropriate graph structures. For example, we can represent molecules by assigning different atoms to different nodes and different chemical bonds to different edges (Prince, 2023). We can model transportation systems, such as road networks, railway systems, and flight routes, using graphs where nodes represent locations (cities, stations, airports), and edges represent the paths connecting them (Rahmani et al., 2023).

GNNs are the preferred neural network topology when it is desired to generate representations of nodes that actually depend on the structure of an underlying graph, as well as any feature information the nodes might have (Hamilton, 2020). More recently, the literature has seen the emergence of a special type of GNN, called spatio-temporal graph neural networks, that are designed to deal with multivariate time series. They have first been applied to the task of traffic prediction (Chen et al., 2020; Li et al., 2017; Wu et al., 2019; Yu et al., 2017; Zheng et al., 2020). While the vanilla GNN architecture is responsible to resolve spatial dependencies among nodes, the temporal dependencies are resolved by the use of recurrent neural networks (Li et al., 2017; Seo et al., 2018) or 1D convolutions (Yan et al., 2018; Yu et al., 2017). Spatio-temporal GNNs take multivariate time series along with an underlying graph structure that describes the relationship among variables as inputs. Unfortunately, raw time-series data is typically not presented with a graph structure that describes the dependence of variables on each other. This structure also needs to be learned from raw time series data.

4.1.1. Formulating Multivariate Time Series with GNN

Following the development in Wu et al. (2020), we let $z_t \in \mathbb{R}^N$ to denote the values of an N-dimensional multivariate time series at the time index t. Daily stock index observations for N countries are arranged in a sequence of P time steps $\mathcal{X} \supseteq \boldsymbol{X} = \{z_{t_1}, z_{t_2}, \dots z_{t_P}\}$. The goal is to predict a sequence of future values $\mathcal{Y} \supseteq \boldsymbol{Y} = \left\{z_{t_{P+1}}, z_{t_{P+2}}, \dots z_{t_{P+Q}}\right\}$. This goal is to be achieved by constructing a map $f : \mathcal{X} \to \mathcal{Y}$ as a spatio-temporal graph neural network by minimizing absolute loss with regularization ℓ_2.

As a reminder, formal definitions of most important graph theory concepts are presented below.

Definition 1 (Graph). *A graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ is a data structure consisting of a set of nodes $\mathcal{V}$ and edges $\mathcal{E}$. The total number of nodes in a graph $\mathcal{G}$ is denoted by N.*

Definition 2 (Neighborhood). *Suppose $u, v \in \mathcal{V}$ and there exists an edge $e = (v, u) \in \mathcal{E}$ pointing from u to v. We say that the*

Table 1: Variable explanations.

Variable	*Explanation*
FTSE MIB	Price performance of the 40 most-traded stock classes on the Borsa Italiana
BIST 100	Price performance of the 100 largest companies on the Istanbul Stock Exchange
CAC 40	Price performance the 40 most significant stocks on the Euronext Paris
FTSE 100	Price performance of 100 most highly capitalised companies listed on the London Stock Exchange
DAX PERFORMANCE	Price performance of 30 biggest German companies that trade on the Frankfurt Exchange
S&P 500	Price performance of 500 of the largest companies listed on stock exchanges in the United States
S&P/TSX	Stock market index representing roughly 70% of the total market capitalization on the Toronto Stock Exchange
IDX COMPOSITE	Index of all stocks listed on the Indonesia Stock Exchange
IPC MEXICO	Weighted measurement index of 35 stocks traded on the Borsa Mexico
NIKKEI 225	Stock market index for the Tokyo Stock Exchange
NSE 30	Price performance of 30 companies on the Nigerian Stock Exchange

Table 2: Descriptive statistics.

Variable	*Source*	*Size*	*Mean*	*Median*	*Standard Deviation*	*Minimum*	*Maximum*	*Skewness*	*Kurtosis*
FTSE MIB	Yahoo Finance	4580	21732	21494	4422.896	12358	35401	0.713	3.590
BIST 100	Yahoo Finance	4580	1969	977	2393.542	541	11194	2.336	7.395
CAC 40	Yahoo Finance	4580	5308	5139	1216.689	2929	8242	0.423	2.417
FTSE 100	Yahoo Finance	4580	6914	7004	644.245	4994	8446	-0.329	2.439
DAX	Yahoo Finance	4580	11990	12101	2865.310	5976	18875	0.112	2.475
S&P 500	Yahoo Finance	4580	2886	2680	1102.271	1278	5644	0.526	2.149
S&P/TSX	Yahoo Finance	4580	16280	15582	2957.038	11310	23105	0.439	2.098
IDX COMPOSITE	Yahoo Finance	4580	5671	5779	961.285	3697	7422	-0.022	1.832
IPC MEXICO	Yahoo Finance	4580	45960	45181	5118.520	33338	58856	0.205	2.407
NIKKEI 225	Yahoo Finance	4580	21605	21103	7127.358	8279	42344	0.376	2.909
NSE 30	Investing	4580	1635	1579	584.534	872	3984	2.095	8.217

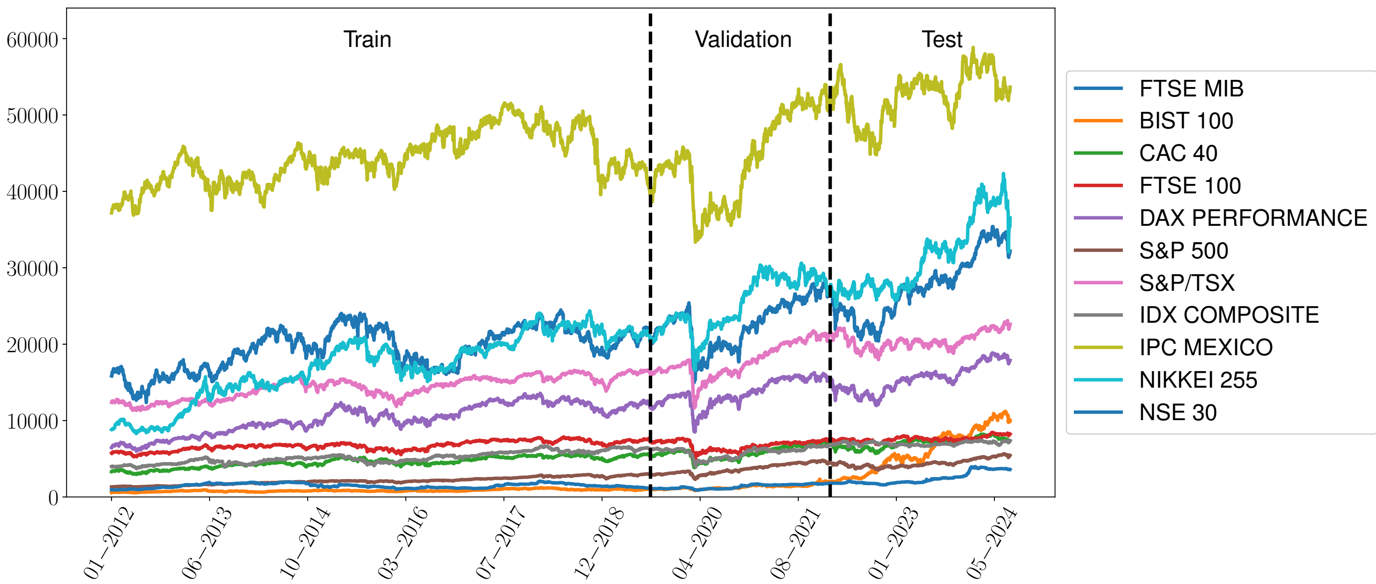

Figure 1: Daily closing price of the stock indices.

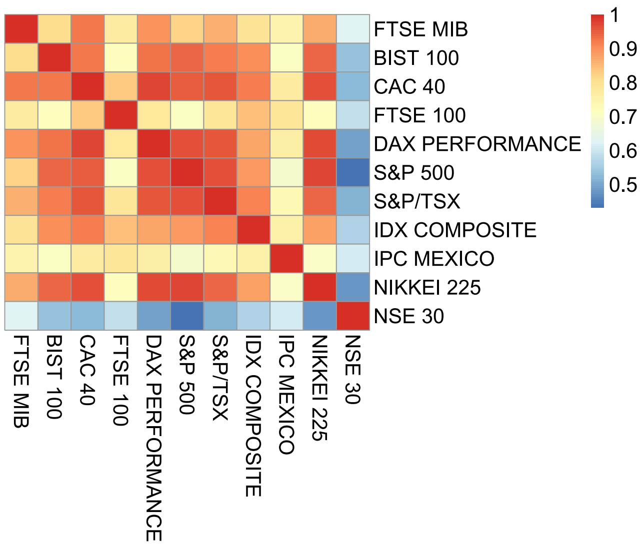

Figure 2: Correlation matrix.

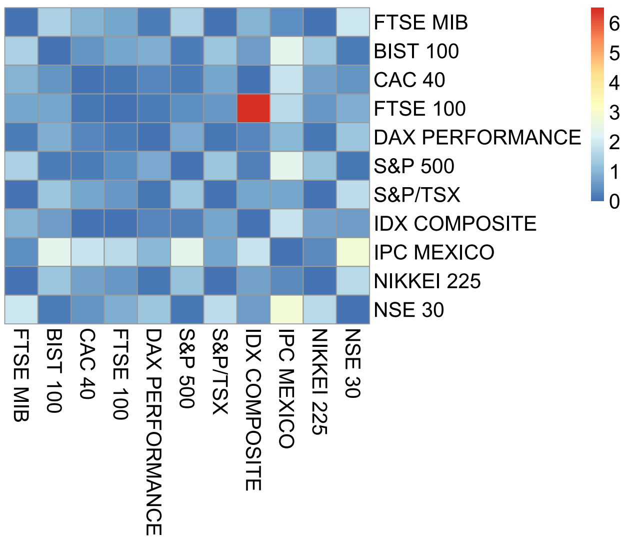

Figure 3: Distance matrix.

set of all such $u \in \mathcal{V}$ constitutes the neighborhood of the node v, denoted by $\mathcal{N}(v) = \{u \in \mathcal{V} : (v, u) \in \mathcal{E}\}$.

Definition 3 (Adjacency Matrix). *The adjacency matrix $\boldsymbol{A} \in \mathbb{R}^{N \times N}$ is constructed such that $\boldsymbol{A}_{ij} > 0$ if and only if there is an edge pointing from v_i to v_j. All other entries are set to zero.*

4.1.2. MTGNN Model Architecture

We borrow the MTGNN model from Wu et al. (2020). In this subsection, we briefly touch upon the most important aspects of this model and invite the reader to the original paper for a more detailed exposition.

The spatio-temporal GNN model operates by embedding the node features in a higher-dimensional space (40 is used in this work). These embeddings are then fed into a graph learning layer, which automatically trains the learnable parameters to compute the graph structure in conjunction with the remaining learnable parameters for prediction. The graph learning layer outputs the current belief on the adjacency matrix at each learning step. This adjacency matrix and the node features are subsequently fed into a sequence of interleaved m graph convolution and m temporal convolution modules. Residual connections are added from the inputs of the temporal convolution to the outputs of the graph convolution modules. Furthermore, each temporal convolution module is followed by skip connections. The residual and skip connections are inserted in order to fight the problem of gradient vanishing. Finally, the final outputs are computed by the output modules, which projects the hidden features to the desired output dimension. Figure 4 provides a demonstration of the full set-up. Readers who are interested in more details on the neural network architecture are invited to peruse (Wu et al., 2020).

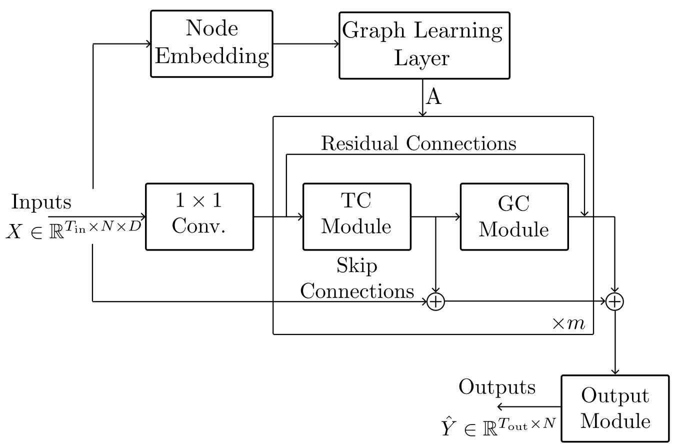

Figure 4: The architecture of the spatio-temporal graph neural network.

4.2. Baseline Forecasting Methods for Comparison

We establish baselines to compare and contrast MTGNN with by measuring the performance of four other prominent methods used to process multivariate time series data. One is the classical autoregressive (AR) model, while the rest are neural-network-based methods: autoregressive-multilayer perception (VAR-MLP), recurrent neural network (RNN-GRU) and temporal convolutional network (TCN).

An autoregressive model assumes that the current value of a time series is a function of its past values. In other words, AR model is when a value from a time series is regressed on previous values from that same time series. In this regression model, the response variable in the previous time period has become the predictor and the errors have usual assumptions about errors in a simple linear regression model. The order of an autoregression is the number of immediately preceding values in the series that are used to predict the value at the present time (Simon and Young, 2024).

The vector autoregressive (VAR) model is a well-known statistical model used to capture linear interdependencies among multiple time series. It has been widely applied in econometrics for modeling and forecasting systems where multiple variables influence each other over time (Lütkepohl, 2005). However, VAR models assume linear relationships, which can be limiting in cases where the underlying data exhibits complex, nonlinear dynamics. To address this limitation, the VAR-MLP model incorporates the MLP, a type of artificial neural network known for its ability to learn and approximate nonlinear functions. By combining VAR with MLP, the VAR-MLP model leverages the strengths of both methods: it captures the linear interdependencies among multiple time series using VAR, while the MLP component models the potential nonlinear relationships that VAR cannot. This hybrid approach allows for more accurate modeling and forecasting in systems where both linear and nonlinear interactions are significant, as demonstrated in empirical studies across various domains, including finance and economics (Zhang, 2003; Zivot and Wang, 2006). The flexibility of VAR-MLP makes it particularly effective in complex systems where traditional linear models may fall short, thus providing a comprehensive framework for time series analysis.

RNNs are a class of neural networks designed to handle sequential data by maintaining a hidden state that captures information from previous inputs (Hochreiter, 1997). However, RNNs suffer from issues like vanishing gradients, which limit their ability to learn long-term dependencies. To address this, the Gated Recurrent Unit (GRU) was introduced as an improved variant of the RNN (Cho, 2014). The GRU uses gating mechanisms—namely, an update gate and a reset gate—to control the flow of information, making it more efficient at capturing dependencies over longer sequences while reducing the complexity (Chung, 2014). This innovation allows GRUs to perform better than traditional RNNs in various sequential modeling tasks by mitigating the vanishing gradient problem and simplifying the model structure.

TCNs are a type of neural network architecture designed for sequence modeling tasks, offering an alternative to Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks. TCNs leverage the strengths of convolutional neural networks (CNNs) by using 1D convolutions to process sequential data, enabling them to capture temporal dependencies over long sequences efficiently. Unlike RNNs, TCNs do not suffer from issues like vanishing gradients and can handle much longer input sequences due to their ability to employ dilated convolutions, which exponentially increase the receptive field of the network without a corresponding increase in computational cost (Bai et al., 2018). Additionally, TCNs use causal convolutions, ensuring that the output at any time step is only influenced by past inputs, maintaining the temporal order of the data (Oord et al., 2016). This structure allows TCNs to outperform traditional RNNs and LSTMs in various tasks, such as time series forecasting, due to their stable training dynamics and ability to capture long-range dependencies (Bai et al., 2018).

4.3. Evaluation metrics

The metrics we used for measuring the performance of various algorithms are relative squared error (RSE), root mean squared error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE). The mathematical expressions for these metrics are given below.

$$\mathrm{RSE} = \frac{\sum_{i=1}^{N} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{N} (y_i - \bar{y})^2}, \tag{1}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{N} (y_i - \hat{y}_i)^2}{N}}, \tag{2}$$

$$\mathrm{MAE} = \frac{\sum_{i=1}^{N} |y_i - \hat{y}_i|}{N}, \tag{3}$$

$$\mathrm{MAPE} = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{y_i - \hat{y}_i}{y_i} \right|, \tag{4}$$

where $\hat{y}_i$ is the value predicted by the algorithm for observation i (out of N observations), y_i is the actual value, and $\bar{y}$ is the average of all target values. For a perfect fit, each of these measures would assume the value 0. Hence, they range from 0 to ∞ with 0 corresponding to the ideal.

Table 3: The hyperparameters of the MTGNN used to train and infer the forecasts.

Hyperparameter	*Value*
Convolution depth	2
Loss	ℓ_1
Dropout	0.3
Convolutional channels	16
Residual channels	16
Skip channels	32
Batch size	8
Epochs	30

5. Results and Discussion

In this section we presented the findings derived from applying MTGNN, and other baseline forecasting methods. Before starting analyses, all historical data values were transformed to natural logarithm. The initial 60% of the dataset used for training the models, the subsequent 20% of the data was used for validation and the last 20% of the data, starting from January 2022 and ending on August 14, 2024 were used for testing purposes.

All the hyperparameters of the MTGNN used to obtain the results are summarized in Table 3.

Once the MTGNN training phase was performed, the constructed graph was shown in Figure 5. In the graph, each node represents the countries' stock indices, and each edge represents the link between them. In this study, we used a convolutional graph network with depth 2. This means that each node had their feature vector updated by considering the current information residing in its 2-hop neighborhood *(i.e., its neighbors and the neighbors of its neighbors)*. The constructed graph should be understood in the sense that 2-hop neighbors have a direct effect on the outcome of each node, and others may only have an indirect effect in predicting the future values of a particular node. Notice that this graph is constructed by performing and end-to-end stochastic gradient descent (more precisely, the Adam optimizer), on the losses accrued between the predicted and the actual values. This means that by no means do we claim that the constructed graph in Figure 5, is a causal one. It is the graph that the optimization has constructed such that the resulting loss is minimized.

The adjacency matrix, corresponding to the graph in Figure 5 is given by **A**. The matrix provides a visual representation of the connections and their strengths between the countries' stock indices. Zeros in the matrix demonstrate no connection between them. According to the adjacency matrix and Figure 5, when we only consider 1-hop neighborhoods, among G7 countries, the US's *(with 7 out-degree connections)*, Germany's and Canada's *(with 5 out-degree connections)* stock indices and among MINT countries, Indonesia's *(with 7 out-degree connections)* and Türkiye's *(with 6 out-degree connections)* stock indices are the most influential ones in the forecasting process. If we consider 2-hop neighborhoods as determined, according to the $\boldsymbol{A}^2$ matrix, among G7 countries, the US's *(with 39 out-degree connections)* and Canada's *(with 34 out-degree connections)* stock indices, and among MINT countries, Indonesia's *(with 31 out-degree connections)* and Türkiye's *(with 25 out-degree connections)* stock indices are the most influential ones in the forecasting process.

$$\boldsymbol{A} = \begin{bmatrix} 0 & 1 & 1 & 0 & 1 & 0 & 0 & 0.98 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0.96 & 1 & 1 & 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 1 & 1 & 0 & 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 1 & 0 & 1 & 0 & 1 & 0.99 \\ 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0.9 & 0 & 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 1 & 0 & 0 \\ 0 & 1 & 1 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0.81 & 1 & 1 & 0 & 0 & 0 & 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 1 & 0 & 1 & 1 & 0 & 0 \end{bmatrix} \quad (5)$$

The results in Table 4 show that the performance of the MTGNN is excellent across all the stock indices of MINT and G7 countries that we considered, with RSE, RMSE, MAE, and MAPE evaluation metrics. When evaluating the second-best results in Table 4, it is obvious that on contrary to MTGNN, the other deep-learning methods RNN-GRU *(second-best model for 2 countries' indices - Italy, Germany)* and TCN *(second-best model for 3 countries' indices - Türkiye, Japan, Nigeria)*, are not as successful as VAR-MLP *(second-best model for 5 countries' indices - France, US, Canada, Indonesia, Mexico)*.

We also have provided a plot of the predictions of the MTGNN, as it is applied to the dataset we set out to test the trained parameters (see Figure 6). The plots in Figure 6 visually show the performance of the MTGNN in predicting the closing prices of each country's stock indices in this test data date range. The performance of the MTGNN is not only satisfactory in terms of its RSE, RMSE, MAE, and MAPE performances, but is also visually pleasing, as can be observed by perusing each plot in the figure.

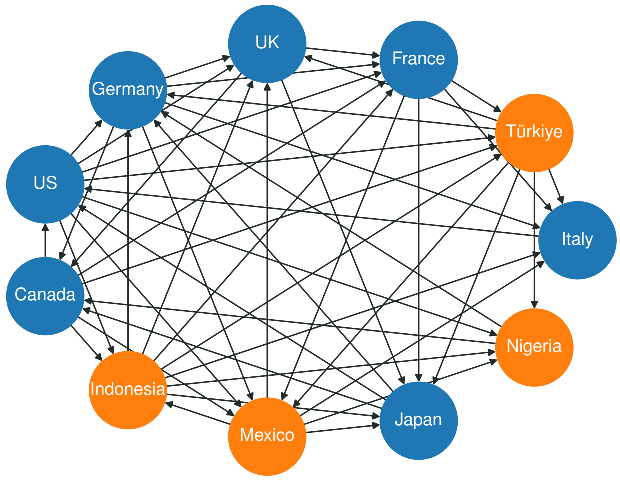

Figure 5: The connectivity of the countries' stock indices deduced by the MTGNN.

Remark 1. *The MTGNN algorithm normalizes the data by subtracting from each column its individual mean and dividing by its individual standard deviation. All data transformations (natural logarithm and normalization) are inverted for the construction of the plots in Figure 6.*

6. Conclusions

While the stock markets of developed countries are still dominant in international markets, the influence of emerging economies has been growing recently. This growth has caused economists to suggest new economic blocs like MINT countries. Although MINT countries are in a growth process, they are quite open to being influenced by advanced economies such as the G7. In particular, emerging economies' stock markets are frequently highly sensitive and closely linked to financial and economic developments in the G7 countries due to the interlinked nature of financial markets. Consequently, it is imperative for investors and policymakers in both developed and emerging markets to comprehend the connections between them, especially in generating forecasts for stock price movement. For this purpose, the stock market indices of G7 countries and MINT countries, representing developed and emerging economies, respectively, were discussed and predicted in the study between 2012 and 2024.

In the study, for the first time, a GNN technique, MTGNN, that allows consideration of spatio-temporal connections in multivariate time series was applied to predict the closing price of the main stock market indices of the economic blocs. Taking into account the countries' complex interconnections, which are not known in advance, in the forecasting process enhances prediction accuracy. It obtained stock price predictions with excellent accuracy via MTGNN, when compared to other AR, VAR-MLP, RNN-GRU, and TCN baseline methods.

Generating forecasts for stock price movements is advantageous for investors, investment managers, and policy-makers engaged in stock market prediction. New artificial intelligence-based deep-learning methods like GNN provide forecasts with unprecedented accuracy even in emerging economies like MINT, which have less stable economic environments and are more sensitive to domestic and global situations than those in developed countries. Future studies should be encouraged to employ these methods more frequently for better predictions in the economics and finance field.

Table 4: Comparison of performances of various algorithms from the literature.

Index	*Algorithm*	*RSE*	*RMSE*	*MAE*	*MAPE*
FTSE MIB (Italy)	AR	3.503	0.276	0.242	2.4%
	VAR-MLP	1.066	0.152	0.125	1.2%
	RNN-GRU	1.005	0.148	1.005	1.1%
	TCN	1.545	0.183	0.174	1.7%
	MTGNN	**0.026**	**0.024**	**0.020**	**0.2**%
BIST 100 (Türkiye)	AR	10.294	1.672	1.600	18.4%
	VAR-MLP	1.487	0.633	0.558	6.4%
	RNN-GRU	0.890	0.492	0.428	4.9%
	TCN	0.439	0.346	0.331	3.8%
	MTGNN	**0.081**	**0.042**	**0.033**	**0.4**%
CAC 40 (France)	AR	6.939	0.237	0.227	2.6%
	VAR-MLP	0.980	0.089	0.076	0.9%
	RNN-GRU	5.589	0.213	0.184	2.1%
	TCN	2.246	0.135	0.133	1.5%
	MTGNN	**0.045**	**0.020**	**0.017**	**0.2**%
FTSE 100 (UK)	AR	0.872	0.040	0.031	0.3%
	VAR-MLP	1.562	0.053	0.046	0.5%
	RNN-GRU	6.76	0.111	0.093	1.0%
	TCN	10.208	0.136	0.133	1.5%
	MTGNN	**0.044**	**0.018**	**0.016**	**0.2**%
DAX PERFORMANCE (Germany)	AR	2.891	0.192	0.175	1.8%
	VAR-MLP	1.017	0.114	0.092	0.9%
	RNN-GRU	0.405	0.072	0.047	0.5%
	TCN	2.706	0.169	0.124	1.9%
	MTGNN	**0.032**	**0.023**	**0.020**	**0.2**%
S&P 500 (US)	AR	10.008	0.357	0.346	4.1%
	VAR-MLP	0.965	0.111	0.092	1.1%
	RNN-GRU	2.879	0.192	0.157	1.9%
	TCN	2.241	0.169	0.163	1.9%
	MTGNN	**0.031**	**0.021**	**0.018**	**0.2**%
S&P/TSX (Canada)	AR	16.568	0.209	0.203	2.0%
	VAR-MLP	1.104	0.054	0.043	0.4%
	RNN-GRU	51.66	0.368	0.337	3.4%
	TCN	5.929	0.125	0.124	1.3%
	MTGNN	**0.024**	**0.020**	**0.017**	**0.2**%
IDX COMPOSITE (Indonesia)	AR	2.812	0.050	0.040	0.5%
	VAR-MLP	1.111	0.031	0.027	0.3%
	RNN-GRU	17.536	0.124	0.117	1.3%
	TCN	66.671	0.241	0.231	2.61%
	MTGNN	**0.037**	**0.016**	**0.014**	**0.2**%
IPC MEXICO (Mexico)	AR	6.134	0.152	0.140	1.3%
	VAR-MLP	0.987	0.061	0.048	0.4%
	RNN-GRU	1.526	0.076	0.068	0.6%
	TCN	7.981	0.173	0.163	1.5%
	MTGNN	**0.021**	**0.022**	**0.018**	**0.2**%
NIKKEI 225 (Japan)	AR	5.273	0.329	0.315	3.0%
	VAR-MLP	1.597	0.181	0.160	1.6%
	RNN-GRU	1.654	0.184	0.148	1.4%
	TCN	0.298	0.078	0.075	0.7%
	MTGNN	**0.025**	**0.025**	**0.020**	**0.2**%
NSE 30 (Nigeria)	AR	6.526	0.747	0.700	8.9%
	VAR-MLP	1.190	0.319	0.292	3.8%
	RNN-GRU	0.491	0.205	0.128	1.6%
	TCN	0.045	0.062	0.057	0.7%
	MTGNN	**0.013**	**0.026**	**0.018**	**0.2**%

The best results are bolded, and the second best results are underlined.

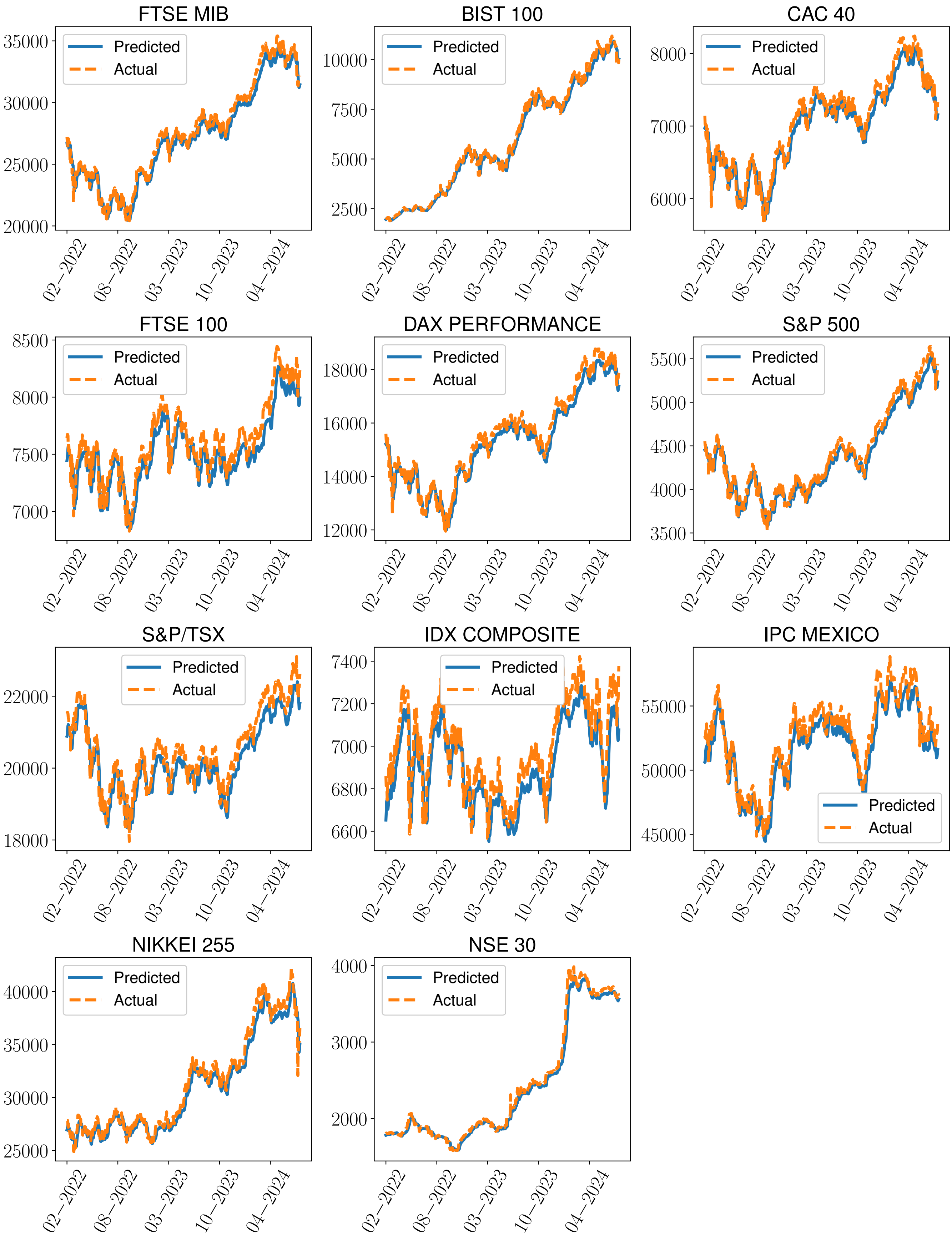

Figure 6: The predictions obtained MTGNN predictor.

References

Acharya, V., Bhadury, S., Surti, J., 2020. Financial vulnerability and risks to growth in emerging markets (no. w27411).

Alkhatib, K., Khazaleh, H., Alkhazaleh, H.A., Alsoud, A.R., Abualigah, L., 2022. A new stock price forecasting method using active deep learning approach. Journal of Open Innovation: Technology, Market, and Complexity 8, 96.

Bai, S., Kolter, J.Z., Koltun, V., 2018. An empirical evaluation of generic convolutional and recurrent networks for sequence modeling. arXiv preprint arXiv:1803.01271 .

Binkowski, M., Marti, G., Donnat, P., 2018. Autoregressive convolutional neural networks for asynchronous time series, in: International Conference on Machine Learning, PMLR. pp. 580–589.

Boesler, M., 2013. The economist who invented the brics just invented a whole new group of countries: The mints. URL: https://www.businessinsider.com/jim-oneill-presents-the-mint-economies-2013-11.

Cakra, Y.E., Trisedya, B.D., 2015. Stock price prediction using linear regression based on sentiment analysis, in: 2015 international conference on advanced computer science and information systems (ICACSIS), IEEE. pp. 147–154.

Cao, B., Zhao, J., Lv, Z., Gu, Y., Yang, P., Halgamuge, S.K., 2020. Multiobjective evolution of fuzzy rough neural network via distributed parallelism for stock prediction. IEEE Transactions on Fuzzy Systems 28, 939–952.

Chen, L., Chen, D., Shang, Z., Wu, B., Zheng, C., Wen, B., Zhang, W., 2023. Multi-scale adaptive graph neural network for multivariate time series forecasting. IEEE Transactions on Knowledge and Data Engineering 35, 10748–10761.

Chen, M.Y., Chen, B.T., 2015. A hybrid fuzzy time series model based on granular computing for stock price forecasting. Information Sciences 294, 227–241.

Chen, W., Chen, L., Xie, Y., Cao, W., Gao, Y., Feng, X., 2020. Multi-range attentive bicomponent graph convolutional network for traffic forecasting, in: Proceedings of the AAAI conference on artificial intelligence, pp. 3529–3536.

Chen, W., Jiang, M., Zhang, W.G., Chen, Z., 2021. A novel graph convolutional feature based convolutional neural network for stock trend prediction. Information Sciences 556, 67–94.

Chen, Y., Xie, Z., 2022. Multi-channel fusion graph neural network for multivariate time series forecasting. Journal of Computational Science 64, 101862.

Cheng, C.H., Chen, T.L., Wei, L.Y., 2010. A hybrid model based on rough sets theory and genetic algorithms for stock price forecasting. Information Sciences 180, 1610–1629.

Cho, K., 2014. Learning phrase representations using rnn encoder-decoder for statistical machine translation. arXiv preprint arXiv:1406.1078 .

Chong, E., Han, C., Park, F.C., 2017. Deep learning networks for stock market analysis and prediction: Methodology, data representations, and case studies. Expert Systems with Applications 83, 187–205.

Chung, J., 2014. Empirical evaluation of gated recurrent neural networks on sequence modeling. arXiv preprint arXiv:1412.3555 .

Cui, Y., Zheng, K., Cui, D., Xie, J., Deng, L., Huang, F., Zhou, X., 2021. Metro: a generic graph neural network framework for multivariate time series forecasting. Proceedings of the VLDB Endowment 15, 224–236.

Deng, S., Zhang, N., Zhang, W., Chen, J., Pan, J.Z., Chen, H., 2019. Knowledge-driven stock trend prediction and explanation via temporal convolutional network, in: Companion proceedings of the 2019 world wide web conference, pp. 678–685.

Durotoye, A., 2014. The mint countries as emerging economic power bloc: Prospects and challenges. Developing Country Studies 4, 1–9.

Dyvik, E., 2024. G7 countries' combined gross domestic product (gdp) as share of the world's gdp from 2000 to 2023. URL: https://www.statista.com/statistics/1372791/g7-combined-gdp-share-world/.

Economics, W., 2024. G7. URL: https://www.worldeconomics.com/Regions/G7/.

Fama, E.F., 1970. Efficient capital markets. Journal of finance 25, 383–417.

Fratzscher, M., 2012. Capital flows, push versus pull factors and the global financial crisis. Journal of International Economics 88, 341–356.

Gao, P., Zhang, R., Yang, X., 2020. The application of stock index price prediction with neural network. Mathematical and Computational Applications 25, 53.

Gulzar, H.M., 2018. Comprehensive Guide to Dynamic Time Warping in Python. Lambert Academic Publishing.

Hamilton, W.L., 2020. Graph representation learning. Morgan & Claypool Publishers.

Hargreaves, C.A., Leran, C., 2020. Stock prediction using deep learning with long-short-term-memory networks. International Journal of Electronic Engineering and Computer Science 5, 22–32.

He, Z., Zhao, C., Huang, Y., 2022. Multivariate time series deep spatiotemporal forecasting with graph neural network. Applied Sciences 12, 5731.

Hiransha, M., Gopalakrishnan, E.A., Menon, V.K., Soman, K., 2018. Nse stock market prediction using deep-learning models. Procedia computer science 132, 1351–1362.

Hochreiter, S., 1997. Long short-term memory. Neural Computation MIT-Press .

Hou, X., Wang, K., Zhong, C., Wei, Z., 2021. St-trader: A spatial-temporal deep neural network for modeling stock market movement. IEEE/CAA Journal of Automatica Sinica 8, 1015–1024.

Izzeldin, M., Hassan, M.K., Pappas, V., Tsionas, M., 2019. Forecasting realised volatility using arfima and har models. Quantitative Finance 19, 1627–1638.

Jarrett, J.E., Kyper, E., 2011. Arima modeling with intervention to forecast and analyze chinese stock prices. International Journal of Engineering Business Management 3, 17.

Jin, M., Zheng, Y., Li, Y.F., Chen, S., Yang, B., Pan, S., 2022. Multivariate time series forecasting with dynamic graph neural odes. IEEE Transactions on Knowledge and Data Engineering 35, 9168–9180.

Karazmodeh, M., Nasiri, S., Hashemi, S.M., 2013. Stock price forecasting using support vector machines and improved particle swarm optimization. Journal of Automation and control engineering 1, 173–176.

Li, Y., Yu, R., Shahabi, C., Liu, Y., 2017. Diffusion convolutional recurrent neural network: Data-driven traffic forecasting. arXiv preprint arXiv:1707.01926 .

Liu, Y., Liu, Q., Zhang, J.W., Feng, H., Wang, Z., Zhou, Z., Chen, W., 2022. Multivariate time-series forecasting with temporal polynomial graph neural networks. Advances in neural information processing systems 35, 19414–19426.

Long, J., Chen, Z., He, W., Wu, T., Ren, J., 2020. An integrated framework of deep learning and knowledge graph for prediction of stock price trend: An application in chinese stock exchange market. Applied Soft Computing 91, 106205.

Lütkepohl, H., 2005. New Introduction to Multiple Time Series Analysis. Springer-Verlag.

Ma, C., Xiao, S., Ma, Z., 2018. Investor sentiment and the prediction of stock returns: a quantile regression approach. Applied Economics 50, 5401–5415.

Mensi, W., Hammoudeh, S., Reboredo, J.C., Nguyen, D.K., 2014. Do global factors impact brics stock markets? a quantile regression approach. Emerging Markets Review 19, 1–17.

Muller, M., 2007. Dynamic time warping in information retrieval for music and motion. Dynamic time warping Information retrieval for music and motion , 69–84.

Nagashybayeva, G., 2020. Research guides: Mint: Sources of economic information. URL: https://guides.loc.gov/mexico-indonesia-nigeria-turkey.

Nasiri, H., Ebadzadeh, M.M., 2023. Multi-step-ahead stock price prediction using recurrent fuzzy neural network and variational mode decomposition. Applied Soft Computing 148, 110867.

Nations, U., 2022. World investment report. URL: https://unctad.org/publication/world-investment-report-2022.

Newland, 2014. The fresh challenge of the mint countries. URL: https://newlandchase.com/the-fresh-challenges-of-the-mint-countries-immigration/.

Nikou, M., Mansourfar, G., Bagherzadeh, J., 2019. Stock price prediction using deep learning algorithm and its comparison with machine learning algorithms. Intelligent Systems in Accounting, Finance and Management 26, 164–174.

Ning, Y., Wah, L.C., Erdan, L., 2019. Stock price prediction based on error correction model and granger causality test. Cluster Computing 22, 4849–4858.

Okoroafor, R., 2024. Mint: meaning, history and economic overview. URL: https://www.makemoney.ng/mint.

Oord, A.v.d., Dieleman, S., Zen, H., Simonyan, K., Vinyals, O., Graves, A., Kalchbrenner, N., Senior, A., Kavukcuoglu, K., 2016. Wavenet: A genera-

tive model for raw audio. arXiv preprint arXiv:1609.03499 .
Pahlawan, M.R., Riksakomara, E., Tyasnurita, R., Muklason, A., Mahananto, F., Vinarti, R.A., 2021. Stock price forecast of macro-economic factor using recurrent neural network. IAES International Journal of Artificial Intelligence 10, 74.
Prince, S.J., 2023. Understanding deep learning. MIT press.
Rahmani, S., Baghbani, A., Bouguila, N., Patterson, Z., 2023. Graph neural networks for intelligent transportation systems: A survey. IEEE Transactions on Intelligent Transportation Systems 24, 8846–8885.
Rey, H., 2015. Dilemma not trilemma: the global financial cycle and monetary policy independence. Technical Report. National Bureau of Economic Research.
Sahoo, P., Charlapally, K., 2015. Stock price prediction using regression analysis. International Journal of Scientific & Engineering Research 6, 1655–1659.
Sawhney, R., Agarwal, S., Wadhwa, A., Shah, R., 2020a. Deep attentive learning for stock movement prediction from social media text and company correlations, in: Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pp. 8415–8426.
Sawhney, R., Agarwal, S., Wadhwa, A., Shah, R., 2021. Exploring the scale-free nature of stock markets: Hyperbolic graph learning for algorithmic trading, in: Proceedings of the Web Conference 2021, pp. 11–22.
Sawhney, R., Agarwal, S., Wadhwa, A., Shah, R.R., 2020b. Spatiotemporal hypergraph convolution network for stock movement forecasting, in: 2020 IEEE International Conference on Data Mining (ICDM), IEEE. pp. 482–491.
Seo, Y., Defferrard, M., Vandergheynst, P., Bresson, X., 2018. Structured sequence modeling with graph convolutional recurrent networks, in: Neural Information Processing: 25th International Conference, ICONIP 2018, Siem Reap, Cambodia, December 13-16, 2018, Proceedings, Part I 25, Springer. pp. 362–373.
Setiani, I., Tentua, M.N., Oyama, S., 2021. Prediction of banking stock prices using naive bayes method, in: Journal of physics: Conference series, IOP Publishing. p. 012059.
Shahi, T.B., Shrestha, A., Neupane, A., Guo, W., 2020. Stock price forecasting with deep learning: A comparative study. Mathematics 8, 1441.
Siddiqui, S., Kaur, R., 2023. Assessing market integration between mint and developed economies: evidence from dynamic cointegration. Business Perspectives and Research , 22785337231156244.
Simon, L., Young, D., 2024. Autoregressive models. URL: https://online.stat.psu.edu/stat501/book/export/html/996.
Suharsono, A., Aziza, A., Pramesti, W., 2017. Comparison of vector autoregressive (var) and vector error correction models (vecm) for index of asean stock price, in: AIP Conference Proceedings, AIP Publishing.
Tsai, I.C., 2012. The relationship between stock price index and exchange rate in asian markets: A quantile regression approach. Journal of International Financial Markets, Institutions and Money 22, 609–621.
Tulcanaza Prieto, A.B., Lee, Y.H., 2019. Determinants of stock market performance: Var and vecm designs in korea and japan. Global Business & Finance Review (GBFR) 24, 24–44.
Wu, Z., Pan, S., Long, G., Jiang, J., Chang, X., Zhang, C., 2020. Connecting the dots: Multivariate time series forecasting with graph neural networks, in: Proceedings of the 26th ACM SIGKDD international conference on knowledge discovery & data mining, pp. 753–763.
Wu, Z., Pan, S., Long, G., Jiang, J., Zhang, C., 2019. Graph wavenet for deep spatial-temporal graph modeling. arXiv preprint arXiv:1906.00121 .
Yan, S., Xiong, Y., Lin, D., 2018. Spatial temporal graph convolutional networks for skeleton-based action recognition, in: Proceedings of the AAAI conference on artificial intelligence.
Yu, B., Yin, H., Zhu, Z., 2017. Spatio-temporal graph convolutional networks: A deep learning framework for traffic forecasting. arXiv preprint arXiv:1709.04875 .
Zhang, G.P., 2003. Time series forecasting using a hybrid arima and neural network model. Neurocomputing 50, 159–175.
Zhang, P., Sha, Y., Xu, Y., 2021. Stock market volatility spillovers in g7 and bric. Emerging Markets Finance and Trade 57, 2107–2119.
Zheng, C., Fan, X., Wang, C., Qi, J., 2020. Gman: A graph multi-attention network for traffic prediction, in: Proceedings of the AAAI conference on artificial intelligence, pp. 1234–1241.
Zivot, E., Wang, J., 2006. Modeling financial time series with S-PLUS. volume 2. Springer.