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. The course a particular stock market takes has a substantial impact on the overall state of that nation's economy. Investors in the stock market strive to maximize their earnings by analyzing the market information and taking actions in response (Gao et al., 2020). Efficient market hypothesis 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).

Over the last decades, 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).

The last five years has seen the use of graph neural networks in stock price prediction. 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. 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 effectiveness of graph neural networks in predicting stock prices by capturing complex, non-linear relationships to enhance accuracy and facilitating decision making in financial markets.

Following Wu et al. (2020), this study employs the MTGNN framework to automatically extract the dependencies in the stock market indices of MINT and G7 countries from raw time series data. It has been shown that MTGNN is good at capturing complex, non-linear relationships between variables by representing them as nodes in a graph, which paves the way to making 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) with graph convolution operations.

3. Data

We have selected the main stock market indices to represent the stock market performances of MINT and G7 countries. These indices are summarized in Table 1: FTSE MIB index for Italy, BIST 100 index for Türkiye, 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.

The data we analyzed was the daily closing prices for the indices collected from January 30, 2012 to August 14, 2024, accessed from Yahoo Finance(Yahoo) and Investing(Investing). This date range was selected because the daily values of the Nigerian index NSE 30 is only avalaible from January 30, 2012. Further, the values of the BIST 100 index have been adjusted to reflect the change executed on July 27, 2020. This change removed two zeros from the values of the index on that date. Therefore, we divided the data preceding this date by 100 to adjust for this change.

Table 2 depicts the descriptive statistics of the data. It can be observed that all indices are non-normal, with the BIST 100 and NSE 30 (stock indices of members of MINT countries) indices being the most positively skewed and leptokurtic.

Figure 2 summarizes the relationships between the indices according to the Spearman correlation analysis. Among MINT countries, the least correlated stock was Nigeria's, followed by Mexico, Türkiye, and Indonesia.

Spearman correlation analysis does not take into account the time-dependent relationships between the indices. A more appropriate method to analyze the time-dependent relationships is dynamic time warping (DTW). DTW is a robust approach to determine a measure of distance which can be interpreted as a measure of similarity between two time series, which may vary with 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 (close to 0) indicate that the two time series are more similar. Figure 3 hence suggests that almost all indices show similarity to each other save for the interplay between UK and Indonesia.

The full data may be observed in Figure 1. The deep learning methods we consider in this work was trained on the initial 60% of the data, validated on the next 20%, and tested on the final 20% as depicted in this figure. The data was normalized after getting mapped through a natural logarithm function to have zero mean and unit variance before training the models.

4. Methodology

In this section, we provide 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. We also provide brief discussion of the baseline methods we use for comparison. The range of baselines we consider comprise classical, hybrid, and deep-learning methods.

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 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.*

In MTGNN, each variable in a multivariate time series data is represented as a node in a graph. The edges in the graph represent how the information flows between the nodes.

Table 1: The variables are the main stock indices of MINT and G7 countries.

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 for the main stock indices.

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

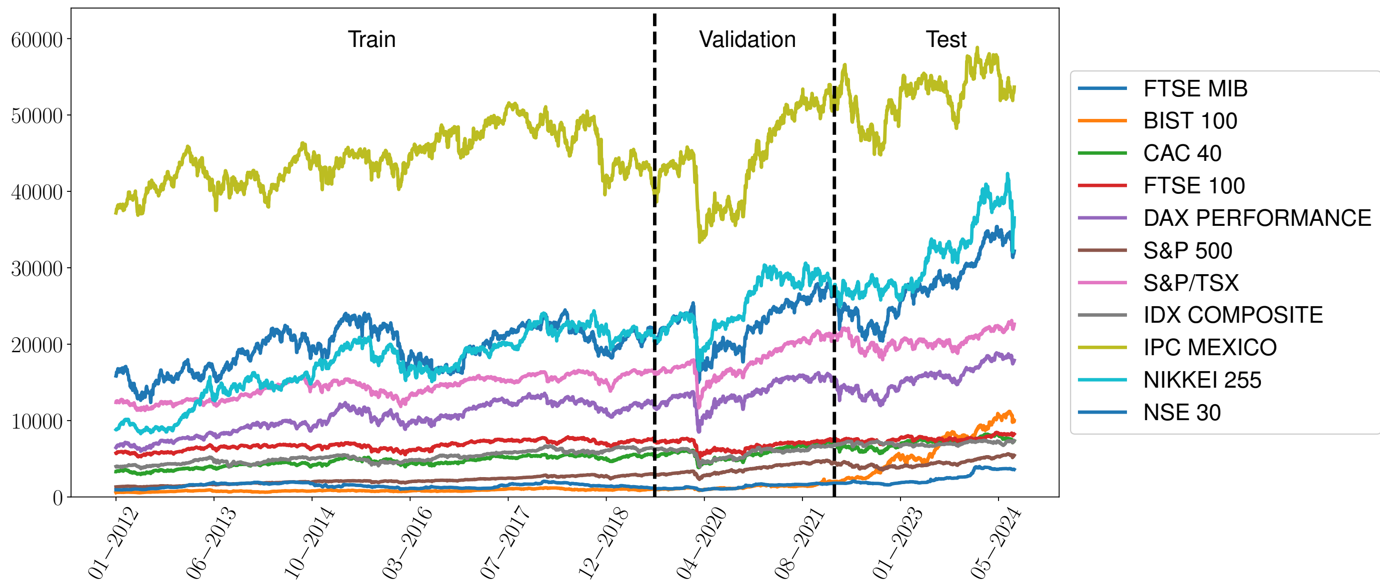

Figure 1: Full glimpse at the processed data: daily closing price of the stock indices.

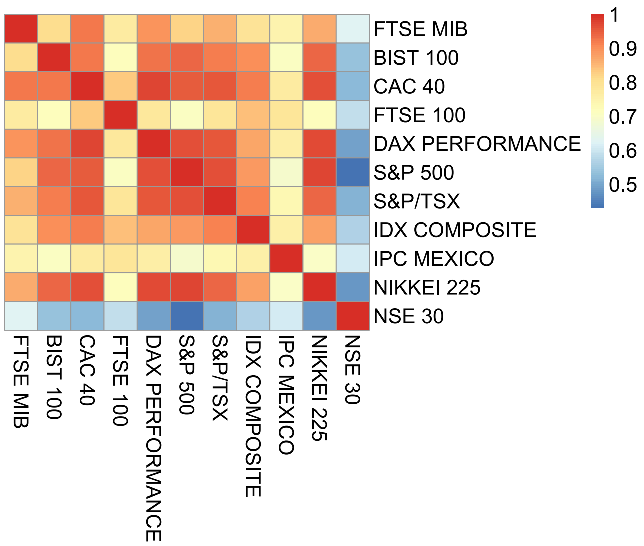

Figure 2: Correlation matrix produced by Spearman correlation analysis.

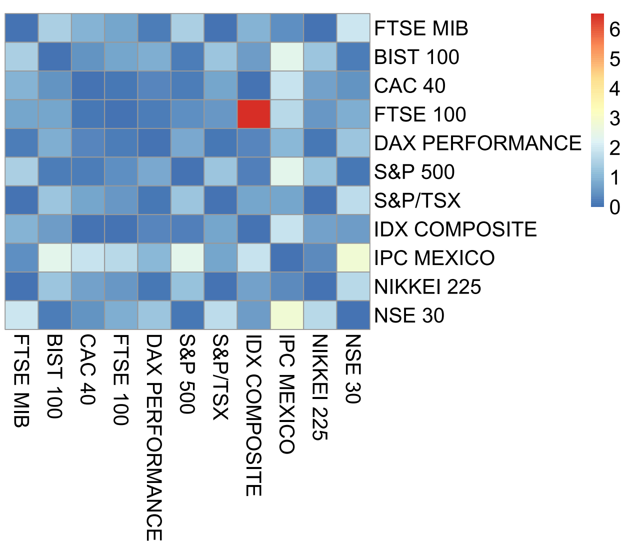

Figure 3: Distance matrix produced by dynamic time warping analysis.

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).

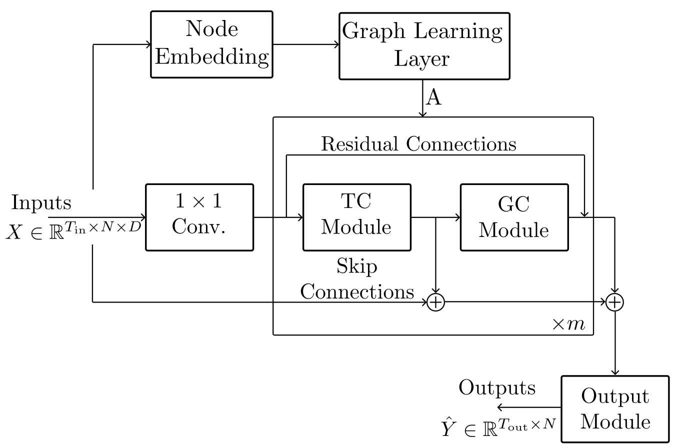

Figure 4: The architecture of the spatio-temporal graph neural network.

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, an AR model regresses on a value from a time series using the previous values of 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 multivariate time series. It has been widely applied in econometrics for modeling and forecasting systems where multiple variables influence each other over time (Lütkepohl, 2005). 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 extends the original VAR using a multilayer perceptron (MLP), which is able to learn to 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. 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).

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). Vanilla RNNs suffer heavily from the vanishing gradient problem, limiting their ability to learn long-term dependencies. To address this, RNNs were equipped with Gated Recurrent Units (GRU) in (Cho, 2014). The GRU uses gating mechanisms to control the flow of information, making it more effective at capturing dependencies over longer sequences (Chung, 2014).

TCN is a type of neural network architecture designed for sequence modeling tasks. They transfer the strengths of convolutional neural networks (CNNs) to learn good representations in image processing to time series by performing 1D convolutions to process sequential data. This mechanism helps TCNs capture temporal dependencies over long sequences efficiently. Unlike RNNs, TCNs do not suffer from vanishing gradients and can handle much longer input sequences by employing dilated convolutions, which exponentially increase the receptive field of the network without a corresponding increase in computational cost (Bai et al., 2018). The convolutions of TCNs are causal, 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). TCNs have been strong competitors of RNNs with long-short term memory (LSTMs) or GRUs in various tasks, including 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.

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

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

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

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

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

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.

5. Results and Discussion

This section presents the results of the experiments conducted to evaluate the performance of the MTGNN in forecasting the stock indices of MINT and G7 countries. The performance of the MTGNN is compared with the performances of the AR, VAR-MLP, RNN-GRU, and TCN models. The results are presented in terms of the RSE, RMSE, MAE, and MAPE evaluation metrics. The best results are bolded, and the second-best results are underlined in Table 4. The hyperparameters of MTGNN used to obtain the results are summarized in Table 3.

After training on the first 60% of the data as shown in Figure 1, MTGNN produces the underlying graph structure that minimizes the ℓ_1 loss as in Figure 5. Recall that, each node of this graph represents the stock index of a country, and each edge represents a link between a pair of stock indices. As shown in Table 3, the depth of the graph convolutions is selected to be 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 in Figure 5 may be interpreted up to 2-hop neighbors have a direct effect on the outcome of each node, while the remaining nodes (variables) 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 $\mathbf{A}$ in equation (5). One may observe the strength of the connections (edges) between pairs of stock indices by examining this matrix. Performing sums over the columns of the adjacency matrix (5) reveals that if only 1-hop neighborhoods are considered, the US, Germany, and Canada are the most influential stock indices among G7 countries with 7, 5, and 5 out-degree connections, respectively. Among MINT countries, Indonesia and Türkiye are the most influential stock indices with 7 and 6 out-degree connections, respectively. Similarly, the out-degrees of the 2-hop neighborhoods may be computed by considering the column sums of the matrix $\boldsymbol{A}+\boldsymbol{A}^2$. In this case, the US and Canada are the most influential stock indices among G7 countries with 39 and 34 out-degree connections, respectively. Among MINT countries, Indonesia and Türkiye are the most influential stock indices with 31 and 25 out-degree connections, respectively.

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

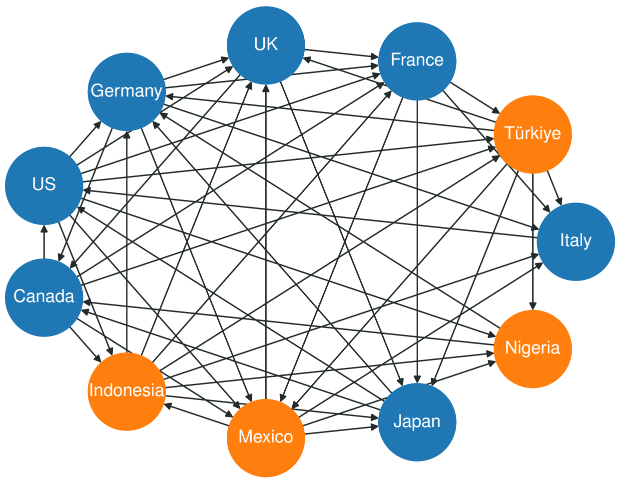

Figure 5: The connectivity of the countries' stock indices deduced by the MTGNN.

Table 4 provides the comparison of the various performance metrics 4.3 over all the algorithms we considered in this work. It can be observed that MTGNN is excellent across all the stock indices. The table shows that the second-best results vary across the board. While RNN-GRU achieves this honor for the indices of two countries (Italy and Germany), TCN is the second-best model for three countries (Türkiye, Japan, and Nigeria) and VAR-MLP is the second-best model for five countries (France, US, Canada, Indonesia, and Mexico).

For completeness, we have provided a plot of the MTGNN's predictions of all the stock indices for the test dataset in Figure 6. 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.

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.

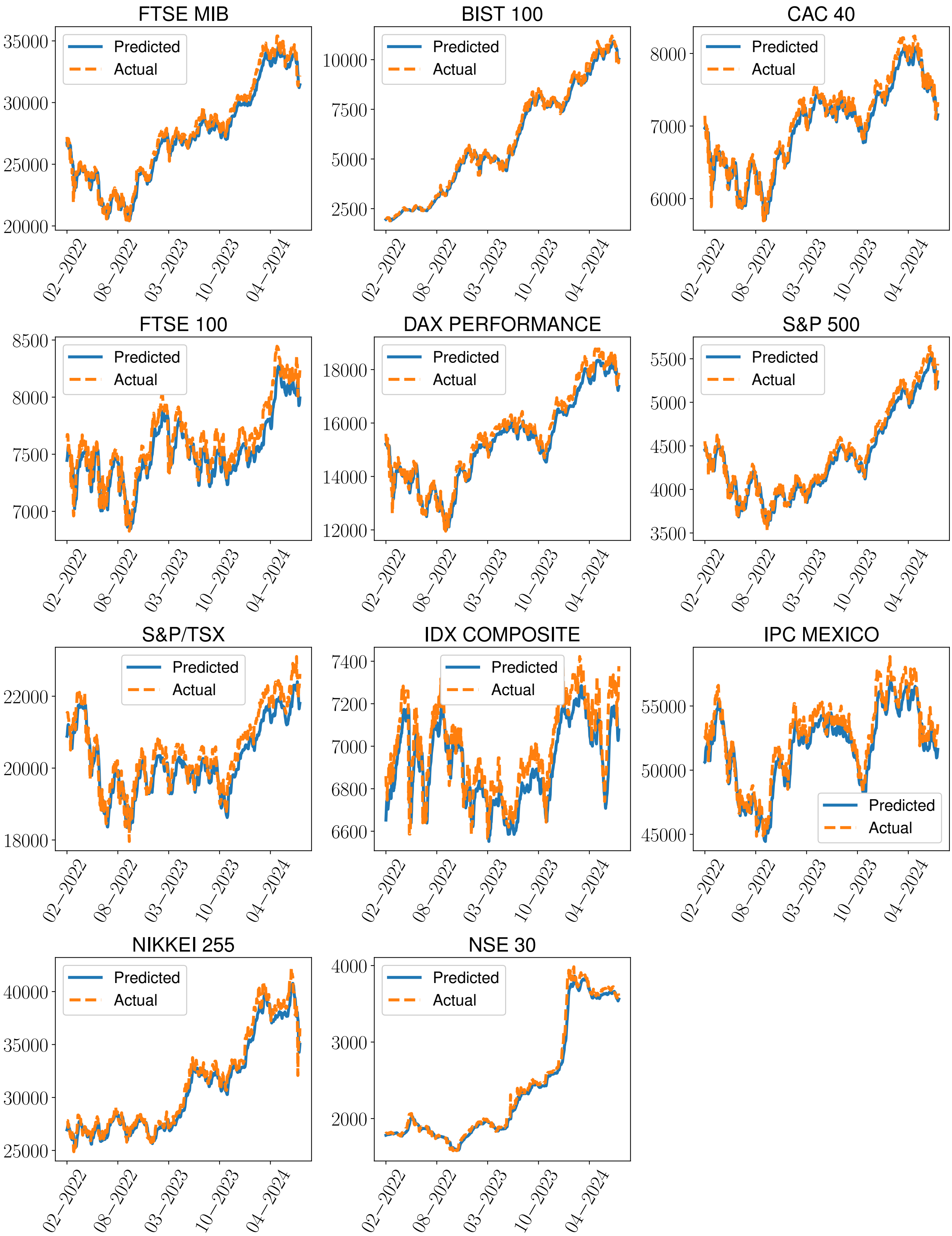

Figure 6: The predictions obtained MTGNN predictor.

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