Available online at www.sciencedirect.com

Borsa İstanbul Review

Borsa İstanbul Review 23-S1 (2023) S30–S39

http://www.elsevier.com/journals/borsa-istanbul-review/2214-8450

Full Length Article

Price prediction of the Borsa Istanbul banks index with traditional methods and artificial neural networks

Ilknur Ulku Armagan

Isparta University of Applied Sciences, Keciborlu Vocational School, Finance Banking and Insurance Department, Isparta, Turkiye

Received 8 October 2023; revised 15 October 2023; accepted 15 October 2023
Available online 18 October 2023

Abstract

In terms of asset size, the banking system constitutes 83% of the financial markets in Turkiye. Given the importance of the banking system in the Turkish capital market, this study offers a price forecasting analysis of the Borsa Istanbul Banks Index, which represents the domestic banking system, between December 27, 1996, to August 31, 2023, using the traditional Autoregressive Integrated Moving Average (ARIMA) Model and two artificial intelligence-based deep learning models, namely, the Facebook Prophet Model (FPM) and Convolutional Neural Networks Model (CNNM). The findings indicate that the CNNM perform better than the other models. The results are useful for researchers working with time series data at the stage of method selection and investment firms and managers that are forecasting future stock price movements. Policy implications of the findings are discussed.
Copyright © 2023 Borsa İstanbul Anonim Şirketi. Published by Elsevier B.V. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

JEL classification: C55; D53; G12; G17; G21

Keywords: Financial markets; Borsa İstanbul banks index; Facebook's prophet model; Convolutional neural networks; Deep learning models

1. Introduction

Developments in the banking system are of great importance for capital markets and national economies. This is because the deposits collected by the banking system from savers are returned to those who demand funds through loans and create resources. These resources are used for consumption, investment or working capital. All these expenditures, on the other hand, contribute to the opening of more enterprises and factories, providing more employment and tax revenues, and thus contributing to the growth of national economies (Schumpeter, 1934).

In this study, I focus on the Turkish Banking System because it makes up a significant portion of the national capital market in asset size. Since the Turkish financial system is a bank-based financial system rather than a market-based financial system, it is inevitable that the regulations made for the financial system are focused on the banking sector through regulatory authorities. While efforts to shape and direct the financial system continue through banks, whether banks use their resources effectively or not is a critical evaluation for the banking system (Kartal, 2018).

There are several other important reasons that indicate the importance of the banking system in the Turkish economy. First, according to 2022 data of the Banking Regulation and Supervision Agency (BRSA) and the Turkish Capital Markets Association (TCMA), the Turkish banking system employ 96% of all working people in all financial institutions (BRSA, 2023; TCMA, 2023). Moreover, in terms of asset size, the share of the banking system in all financial institutions is 83% at the end of 2022 (BRSA, 2023). Therefore, banks that intermediate capital market instruments contribute greatly to the development of capital markets and hence economic development. According to the June 2023 data of BRSA, there are 35 deposit banks, 6 participation banks, 16 development and investment banks in the Turkish banking system. Deposit banks constitute 86% of the banking system. For the first six months of 2023,

E-mail address: ulkuarmagan@isparta.edu.tr.
Peer review under responsibility of Borsa İstanbul Anonim Şirketi.

https://doi.org/10.1016/j.bir.2023.10.005
2214-8450/Copyright © 2023 Borsa İstanbul Anonim Şirketi. Published by Elsevier B.V. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

total asset size of the banks reached TL 19.102 billion, total amount of loans reached TL 10.01 billion, and total amount of deposits and participation reached TL 11.65 billion. Some of the banks operating in the banking system are publicly traded in Borsa Istanbul and included in the Borsa Istanbul Banks Index (BIST Banks Index, XBANKS). As of August 31, 2023, the shares of twelve banks are traded on BIST Banks Index according to the Public Disclosure Platform (2023). Through the publicly traded banks, the banking system have gained further importance for the Turkish capital markets over time.

Since the banking system is an essential element of the capital markets and backbone of the Turkish economy, positive or negative conditions in the banking system are directly reflected in the capital markets and economic activity.[1] The 2001 financial crisis experienced in Türkiye caused financial instability and recession as the economy shrank by 5.8% in 2001. This was the largest negative growth rate ever realized in Türkiye (World Bank, 2023). According to the Banks Association of Türkiye, the ratio of total assets of the banking system to national income in 1999 was 92%, while this ratio declined to 78% in 2002. Due to the crisis, banks failed, bank employees became unemployed, and the total asset size of banks decreased. Therefore, the 2001 crisis originating from the banking system clearly reveals the importance of banks in national capital markets and the Turkish economy.

Today, the traditional view of finance has shifted from merely obtaining funds for the firm into a more comprehensive concept considering all the factors creating value. As such, finance has focused on the goal of maximizing share price for the benefit of shareholders, reflecting all internal and external factors as well as the potential of the firm (Topaloğlu & Karakozak, 2018). Sector indices created by Borsa Istanbul are of great importance as the leading indicators of different sectors measuring cumulative performance of the companies as a group. The sector indices traded in Borsa Istanbul directly measure the positive or negative changes that may occur in the sector and reflect their effects (Kaderli et al., 2013). One of these sector indices is BIST Banks Index (XBANKS). It is an indicator of both the performance of Turkish banking system and the general state of the economy. A strong banking system paves the way for a more stable BIST Banks Index attracting more investors.

Umbrella or broad equity indices are widely used as benchmarks for institutional portfolios. Index investing became a legitimate technique for institutional investors because of the efficient market theory's expanding popularity (Hallerbach, 1994). According to the efficient market hypothesis, all stocks are precisely valued based on their intrinsic investing characteristics and trade at their fair market value on exchanges. According to the argument, the market is supreme and cannot be influenced by any one investor or organization because all market participants have access to the same knowledge. Institutional investors and fund managers must follow the market and have no control over it since stock prices in the market immediately discount all available information. According to the premise, investors make informed decisions about their stock purchases and sales. Even if many market participants are highly irrational or stock prices display higher volatility that is not justified by fundamentals like earnings and dividends, markets can nevertheless be efficient (Fama, 1970).

According to proponents of the efficient market theory, investing in a low-cost, passive portfolio is advantageous for investors. The opponents of the efficient market hypothesis argue that equities can fluctuate from their fair market prices and it is feasible to outperform the market. Market inefficiencies arise for a variety of reasons, including information asymmetries, transaction costs, market psychology, and human emotion. As a result, there may be possibilities for extra gains when certain assets are overvalued or undervalued in the market (Malkiel, 2003).

In this study, I construct a price forecasting model of the index by analyzing the BIST Banks Index. As the banking system in Türkiye represents the foundation of the national capital market, the stability of the banking system, measured by changes in the BIST Banks Index s, closely affects the national economy, and indicates the health of the national capital market. When the study is evaluated through the lenses of the efficient market theory, if investors can forecast index prices, it may give them the ability to outperform the market, indicating that the market may not in fact be efficient.

There are several qualitative and quantitative studies on price forecasting in the literature. Most of the existing studies focus on modeling time series with traditional methods.[2] However, since the relationship between dependent and independent variables in time series modeling is not dynamic and time series contain a lot of uncertainty and error terms, the accuracy of traditional model forecasts is questioned (Yang & Wang, 2019). For this reason, this study uses two artificial intelligence-based deep learning models to achieve better performance. These models have recently come to the forefront with the influence of technology and are becoming more widespread. The fact that the models can only be used with some programming languages limits their use. However, empirical evidence reveals that these models give better results than traditional methods (see Section 3 for related studies and empirical evidence). For this reason, I utilize two artificial intelligence (AI) models, namely, the Facebook Prophet Model (FPM) and Convolutional Neural Networks Model (CNNM), for forecasting of the BIST Banks Index. I also employ the traditional ARIMA model for comparison purposes.

The main contribution of the paper to the literature is the application of the classical method ARIMA together with new AI methods, FPM and CNNM, to predict the Borsa Istanbul Bank index. To the best of my knowledge, this is the first study on the BIST Banks Index using these AI models. My study is closely related to a recent study by Gunduz, Yaslan and

[1] For further discussion of the Turkish banking system and its importance, see, among others, Partovi and Matousek (2019) and Caliskan et al. (2021).

[2] Some of them are regression models, ARIMA Model, Error Correction Model, Decomposition Method, Fuzzy Forecasting Models, and others.

Cataltepe (2017) who employed CNN models to forecast the price of Borsa Istanbul 100 stocks. The difference between my work and theirs is that my study focuses on the BIST Banks index and uses another AI method (FPM), in addition to ARIMA, while they predict Borsa Istanbul 100 stocks. I find that FPM and CNN models perform better compared to the ARIMA model and CNN model provides better forecasts than the FPM model for the BIST Banks Index.

This study is organized as follows. Section 2 provides information about the BIST Banks Index and the banks traded in the index. In section 3, a brief review of the literature is presented. Section 4 provides a short overview of ARIMA, FPM, and CNN models, while Section 5 reports the ARIMA, FPM, and CNNM results. The last section concludes the paper with some policy implications of the findings.

2. BIST banks index

As of August 31, 2023, 12 banks are traded in the BIST Banks Index, which started to be calculated on Dec 27, 1996. Table 1 shows the banks traded in the index and their ticker codes (BIST, 2023; PDP, 2023).

The market capitalization of the BIST Bank Index was TL 1133 billion and the number of investors was 706,791 as of August 31, 2023. Fig. 1 shows the ratio of market capitalization and number of investors of the BIST Bank Index compared to the BIST All Index on the same date. The BIST All Index consists of 515 companies traded in Borsa Istanbul. The market capitalization of the BIST bank index constitutes 10.54% of the entire index, while the number of investors constitutes 10.22% (BIST, 2023).

Fig. 2 shows the daily closing values of the BIST Banks Index from Dec 27, 1996, to August 31, 2023. The index has been gaining value especially since July 2022. The appreciation of the index is approximately 290% in Turkish lira terms.

In addition to the BIST Banks Index, BIST Liquid Banks Index (XLBNK) is traded in Borsa Istanbul. XLBNK started to be calculated on Nov 4, 2019. The index includes 9 companies, namely Akbank, Albaraka Türk Participation Bank, Sekerbank, Garanti Bank, Halkbank, Isbank, Industrial Development Bank of Türkiye, Vakıflar Bank, Yapı ve Kredi Bank (PDP, 2023). The stocks in the index are selected from the most traded stocks in the BIST Banks Index.

Table 1
Listed banks and ticker codes in the BIST Banks Index.

Company Name	Code
AKBANK	AKBNK
ALBARAKA TÜRK PARTICIPATION BANK	ALBRK
ICBC TURKEY BANK	ICBCT
ŞEKERBANK	SKBNK
GARANTİ BANK	GARAN
HALK BANK	HALKB
İŞBANK	ISCTR
İŞBANK	ISATR
İŞBANK	ISBTR
INDUSTRIAL DEVELOPMENT BANK of TURKEY	TSKB
VAKIFLAR BANK	VAKBN
YAPI VE KREDİ BANK	YKBNK

3. Review of literature

This section provides an overview of recent studies that have used different forecasting models using time series data.

There are several studies that have recently used the FPM model. Borneklint (2021) analyzed the prices of Bitcoin and Google stock from Jan 01, 2015, to May 04, 2021, with FPM model and obtained reasonably good forecasts. Garlapati et al. (2021) predicted stock prices for 2021 with FPM and found that there will be an initial appreciation and then a depreciation in 2021. Jackson et al. (2021) made a price forecast for 2021 using the FPM model with 10-year Reliance stock price data and predicted that the stock would appreciate. Yusof et al. (2021) estimated the Standard & Poor's 500 index, Dow Jones Industrial Average Index (DJIA), China Security Index, Kuala Lumpur Composite Index, Hong Kong Hang Seng 300 Index, Nihon Keizai Shinbun Index data with FPM model. They found that the model is consistent with the data and the highest Mean Absolute Percentage Error (MAPE) value found in the model is 6%. Using Non-Fungible Token (NFT) market volume information from June 23, 2017, to Oct 01, 2021, Oncu (2021) found that the market will appreciate in 2022 with FPM.

Other studies used the FPM model along with other models. Güleryüz and Özden (2020) forecasted the crude oil prices with the FPM model and Long Short-Term Memory (LTSM) models using crude oil price data for the period 1988–2020. In the study, while crude oil prices are predicted to depreciate, better results are obtained with the LTSM model. Usher and Dondio (2020) estimated the price movements of the British pound (GBP) with the ARIMA Model and FPM. When the results of the models are compared, unlike other studies, the ARIMA Model provided better forecasting results than the FPM. Toharudin et al. (2020) predicted air temperatures with LTSM and FPM. The results show that FPM predicts the minimum air temperature better, while LTSM predicts the maximum air temperature better. Fang et al. (2019, pp. 1–2) forecasted the MSCI Taiwan Index Futures exchange index with LTSM and FPM models from Jan 1, 2014, to Dec 31, 2018. The forecasts are augmented with the Back Propagation Neural Network (BPNN) Model. The results showed the successful performance of the latter model.

There are limited studies that have used the CNN model. Li (2021) made a short-term forecast using the CNNM, using the Shanghai Stock Exchange Index and Shenzhen Stock Exchange Index between 2015 and 2019. Unlike the traditional models that make standard forecasts, by adding investor sentiment to the model, he found that changes in the stock index can be better predicted. Another study that also used the CNN model and is closely related to my study is Gunduz et al. (2017) who predicted Borsa stock prices of the 100 companies listed in BIST 100 Index using hourly intraday data between January 2011 and December 2015. They used two types of CNN models. The first model (CNN1) used randomly ordered features, while the second model (CNN2) utilized features

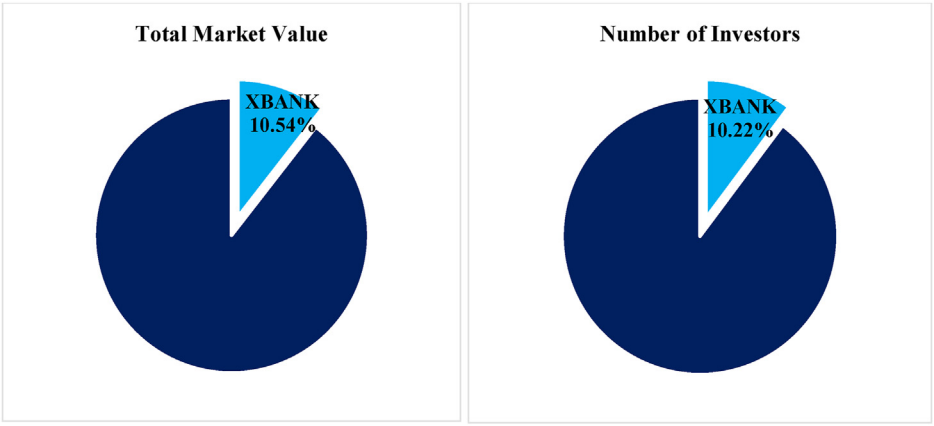


Fig. 1. Market capitalization and number of investors of the BIST bank index compared to the BIST all index as of August 31, 2023.

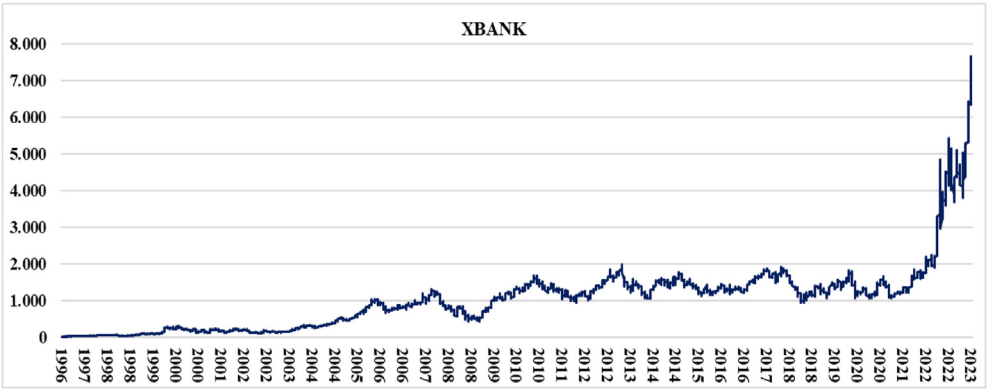


Fig. 2. Daily closing values of the BIST banks index from Dec 27, 1996, to August 31, 2023.

based on 25 technical indicators, price, and temporal knowledge. They divided the sample period into two parts. The first part included a training set from January 2011 to December 2014), while the second part was used for testing from January 2015 to December 2015. The performance of CNN1 and CCN2 models are compared with the performance of Logistic Regression. They found that CNN2 model did the best prediction of BIST 100 Index prices. In this study, I extend Gunduz et al. (2017)'s research by using both FPM and CNN models to predict the BIST Banks Index using a more recent sample period (1996–2023).

In general, when the above studies in the literature are evaluated, it is seen that artificial intelligence-based models performed better than traditional or other models. Therefore, this study uses the FPM and CNNM to test whether they also provide better forecasting results for the BIST Banks Index than the traditional ARIMA model.

4. Forecasting methods: a brief description

One of the methods used in the estimation of time series is the ARIMA model. Time series are non-stationary series whose variance and mean change over time (Gujarati, 1995). This is because the series often exhibits trends, seasonality or cyclical fluctuations and irregular movements (Newbold et al., 2003). Therefore, to avoid the problem of spurious regression in the modeling of the series, the series should first be stationary. Differentiation, integration, I(d) process is performed to make the series stationary. Here d gives the degree of differencing. After the series has been made stationary, the autocorrelation function that gives the correlation between the series itself and its lags and the partial autocorrelation function that gives the lags between the lagged values are examined. Among the functions, there is the Autoregressive Model, AR(p), which gives the relationship between the values of the series and their past values and the Moving Average Model, MA(q), which gives the relationship between the error terms of the series and their past error terms. In the model, p is the number of lags and q is the number of moving averages (Box & Jenkins, 1976; Box & Pierce, 1970).

The model is generally more successful in short-term forecasts. Angadi and Kulkarni (2015) suggest the use of the ARIMA model for short-term forecasting of time series such as stock prices and show that the model performs better in short-term forecasting. Similarly, Banarjee (2014), using the monthly closing data of the Indian Stock Exchange stock index between 2007 and 2012, employed the ARIMA model for short-term forecasting and found that ARIMA (1,0,1) is the most appropriate model when compared with other models.

The FPM model automatically adds linear and non-linear functions to the model. Outliers such as missing data, sudden rises and falls in the series or changes such as trend and seasonality are also corrected by the model. Thus, forecasts are made with the model obtained for the desired period. FPM Model is an open-source library developed by the Facebook data science team in 2017. The model enables forecasting for non-linear time series with Python and R programs. The model is based on mathematical Fourier series. The FPM consists of growth, seasonality, holidays, and an error term as shown in Equation (1).

$$y_t = g_t + s_t + h_t + \varepsilon_t \quad (1)$$

where g_t represents growth, s_t is seasonality, h_t is holidays and ε_t is the error term. Since the model forecasts by adding these terms, it makes a more precise assessment. The model makes better predictions in series with trend, seasonality, and missing data (Taylor & Letham, 2018; Upadhayula et al., 2019). The model automatically detects changes in the trend by finding the change points in the series, seasonality effect with Fourier series, and missing data with dummy variables.[3]

The CNN model was created in 1998 by Lecun et al. (1998) as a feed-forward neural network model. In the model, local perception and weight sharing reduce the number of parameters and increase the efficiency of the learning process. The model consists of a convolution layer and a pooling layer. Each convolution layer contains many convolution kernels. Thus, the features of the data are learned. However, due to the large number of features, the training time of the model becomes longer. Therefore, to train the model more quickly, the second part of the model, the pooling layer, is used and classification is performed with full connectivity. Thus, the forecasting model is completed (Lecun et al., 1998).[4] The CNN model is effective in time series forecasting.

5. Prediction of the BIST banks index with ARIMA, FPM and CNN models

For the analysis, the daily closing prices of the BIST Banks Index (XBANKS) index from Dec 27, 1996, to August 31, 2023, are used. Dataset is obtained from Borsa Istanbul Historical and Reference Data Platform Datastore (BIST, 2023).

In all models, the data were divided into a training set and a test set, with 80% of the data used for training and 20% for testing. Thus, a training data set containing inputs and outputs and a test data set containing only inputs were created. Selected models were used to learn the historical data and predict the future price value of the BIST Banks Index. The Coefficient of Determination, R-Squared (R^2) and the Mean Absolute Percentage Error (MAPE) parameters are used to test the accuracy of the models. The model with the lowest prediction error (residuals) u_t, which is the difference between the prediction values and the actual values, is considered to have the best performance. Therefore $u_t = y_t - \hat{y}_t$ should be $\sum_{t=1}^{n} u_t = 0$. R-Squared and MAPE are computed as follows:

$$R^2 = 1 - \frac{\sum_{t=1}^{n} [y_t - \hat{y}_t]^2}{\sum_{t=1}^{n} [y_t - \bar{y}_t]^2}$$

$$MAPE = \sum_{t=1}^{n} \frac{|u_t|}{y_t} \times \frac{100}{n}, y_t \neq 0$$

where n represents the number of samples, y_t represents the actual value, $\hat{y}_t$ represents the predicted value, and $\bar{y}_t$ average value of the actual value.

R^2 parameter, which ranges between 0 and 1, gives the level of appropriateness of the model to the variable it aims to explain. The closer the value of the parameter to 1, the higher the fit of the model to the variable it seeks to explain (Gujarati, 1995). When the MAPE parameter value is less than 10% it indicates that the performance of the prediction model has a high degree of accuracy, between 10% and 20% indicates that the model is good, and between 20% and 50% indicates that the model is acceptable, and above 50% indicates that the prediction model is faulty. The MAPE value is measured as a percentage (Smith & Johnson, 2020).

In the analysis, ARIMA model was estimated using the Pandas library of Phyton program. The Phyton program tests the stationarity of the time series of the BIST Banks Index. Pyhton programme takes the logarithm of the data used in the model and turns it into a stationary series if needed. The graphical outputs of the programme are based on the learning and testing model, this is the reason why the time series of the BIST Banks Index in the figures may not look stationary. Because the programme creates a whole graph from the whole process.

The Pandas library performs data loading and storage, data cleaning and editing, data indexing and selection. Numpy from the Phyton library was used for calculations. Statsmodels.tsa.arima.model is the main library for the ARIMA forecasting model. Optuna is an optimization parameter for large data. This automatically provides the correct result instead of manual trial and error. Results were converted to DataFrame and figures were prepared with matplotlib.pyplot module. Sklearn.model is a library of machine learning algorithms in Python. Thus, machine learning models can be created and trained.

Before estimating the model, the accuracy of the data imported into Python was tested with the first five lines and figures of the data. After data verification, the best prediction model for the ARIMA model was searched with the Optuna optimization parameter. The most appropriate model was found to be $p = 1, d = 0, q = 1$ and the ARIMA (1,0,1) model was created. Fig. 3 shows the comparison of the 20% test data of the model with the real data.

[3] See Taylor and Letham (2017) and Sharma et al. (2022) for further information about the FPM model and its assumptions.

[4] See Lecun et al. (1998), Gunduz et al. (2017), and Indolia et al. (2018) for further information about the CNN Model and its assumptions.

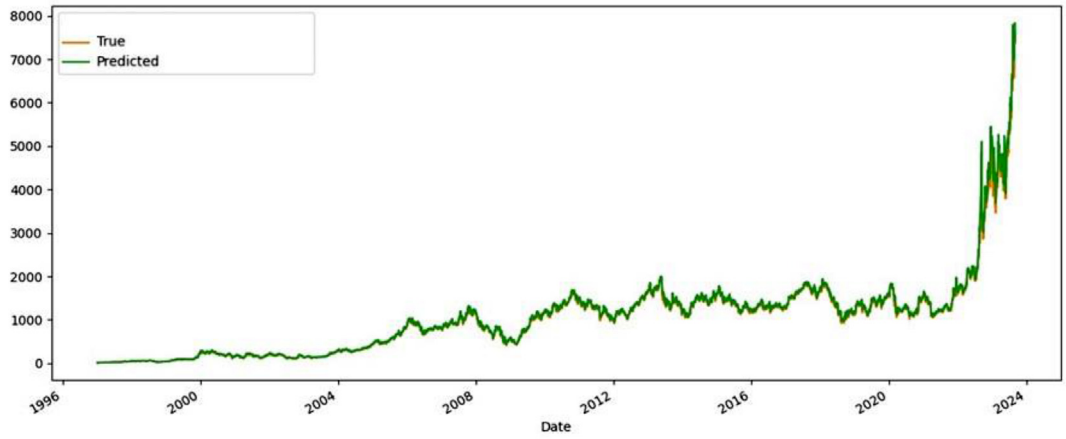


Fig. 3. Comparison of 20% test data generated with ARIMA model with real data.

To test the ARIMA (1,0,1) model, the values of the MAPE and R-Square parameters were calculated. The MAPE value of the model was found to be 25%. The R-Square statistic of the model was $R^2 = 0.30$. After the parameters calculated to test the accuracy of the model, the annual forecast obtained by training the ARIMA (1,0,1) model with 80% of the entire data since 1996 is given in Fig. 4. The data shows that XBANKS will follow a flat course for 2024.

When the ARIMA (1,0,1) model is modeled for the period before July 2022 when the trend change is detected, the MAPE value of the model is 26.01%. The R-Square statistic of the model is $R^2 = 0.62$. The annual forecast obtained by training 80% of the entire data from Dec 27, 1996, to July 05, 2022, with the ARIMA (1,0,1) model shows that the XBANKS will lose value for the next year. The forecast data is given in Fig. 5.

When the forecasts generated for two different periods are compared, the model trained using all data predicts a sideways movement in its one-year forecast, while the model trained until July 2022, when the trend change begins, predicts a depreciation in its one-year forecast.

The Facebook Prophet Model (FPM) similarly uses the Pandas library of the Phyton program for analysis. Pandas is used for data manipulation and data analysis, processing data quickly and efficiently using dataframes. Prophet is an open-source time series analysis library for modeling and forecasting time series data. Prophet provides automatic detection of trends and seasonality, modeling for special cases and holidays, daily, monthly, annual data sets, missing data fitting, model flexibility, and fast forecasting. Matplotlib.pyplot module was used for figures and numpy for calculations. Sklearn.model was again preferred to train the model. Sklearn.metrics performs pre-data processing, model selection and validation, model training and prediction, valuation, component analysis and dimension reduction, data set splitting.

As with the ARIMA model, the accuracy of the data imported into Python was tested with the first five rows and figures of the data before proceeding to model estimation in FPM. In the model, 80% of the data was used for training and 20% for testing, and the evaluation criteria MAPE and R Square parameters were calculated.

The MAPE of the model is 34.44%, while the R-Square value is 0.82. The one-year forecast obtained by training the FPM with 80% data is given in Fig. 6. The model estimated after the training data shows that the index, which has experienced a rapid increase in value, will lose value for the next year.

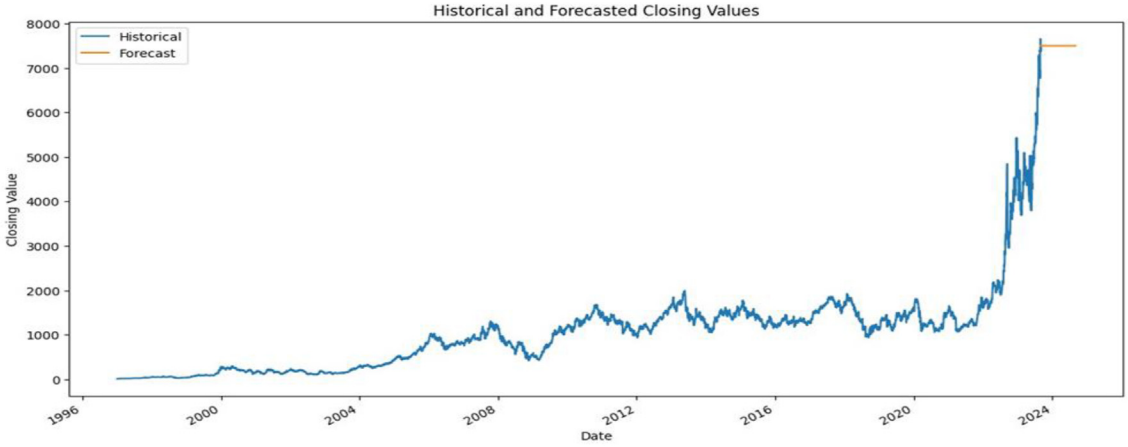


Fig. 4. 1-Year forecast obtained by training the ARIMA (1,0,1) model.

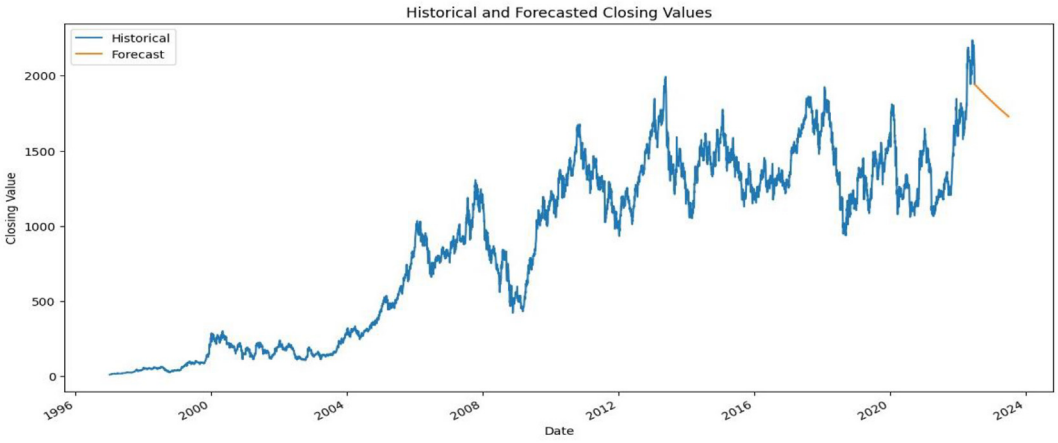


Fig. 5. 1-Year forecast obtained by training the ARIMA (1,0,1) model.

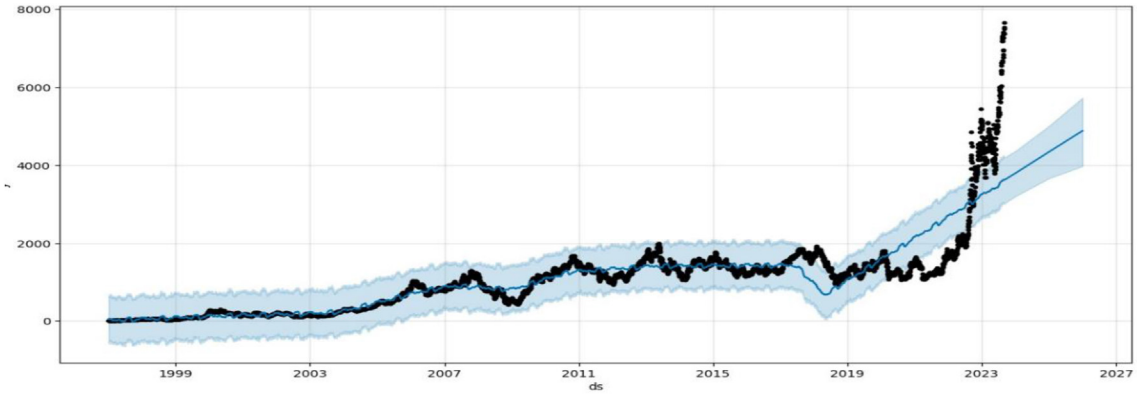


Fig. 6. 1-Year forecast obtained by training FPM

The critical breakpoints of the model identified by training the FPM are shown in Fig. 7. At these points, trend changes occur in the series.

For the CNN Model, the tensorflow.keras library with the actual model was used in the Python program. Data analysis tools were implemented using the Pandas library. Numpy was preferred for calculations in the model. Figures were created using matplotlib.pyplot. Sklearn library containing machine learning algorithms was used in the program.

In the CNN model, the accuracy of the data applied to the program was checked with the first five lines and figures and the analysis was started. For the prediction model, learning model algorithms were created using 80% data. Finally, figure algorithms were created, and predictions were made for the learned period and the following year. Fig. 8 shows the comparison of the 20% test data generated from the model with the real data.

After training the model and determining the accuracy of the trend in the tested part, a one-year forecast was made for the

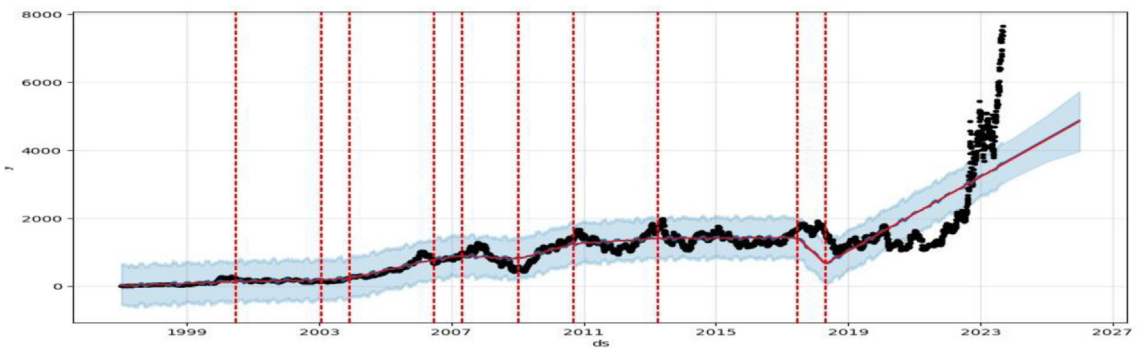


Fig. 7. Critical breakpoints detected by FPM training.

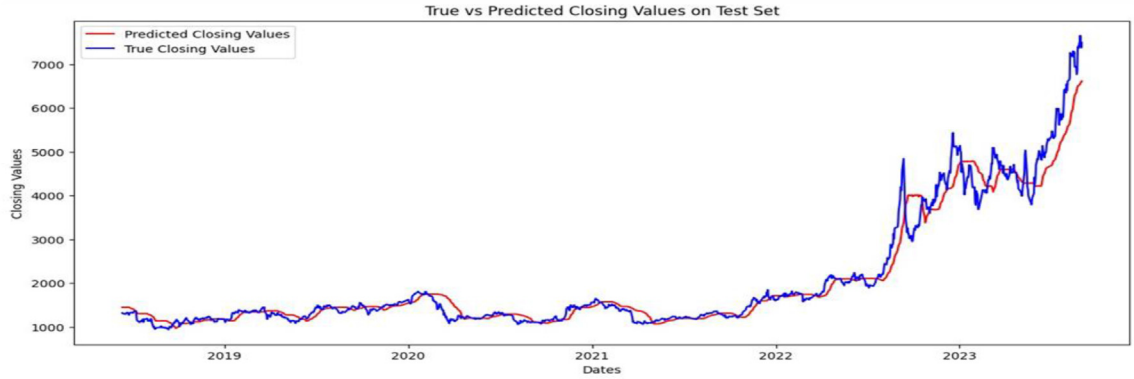


Fig. 8. Comparison of 20% test data generated with CNN model with real data.

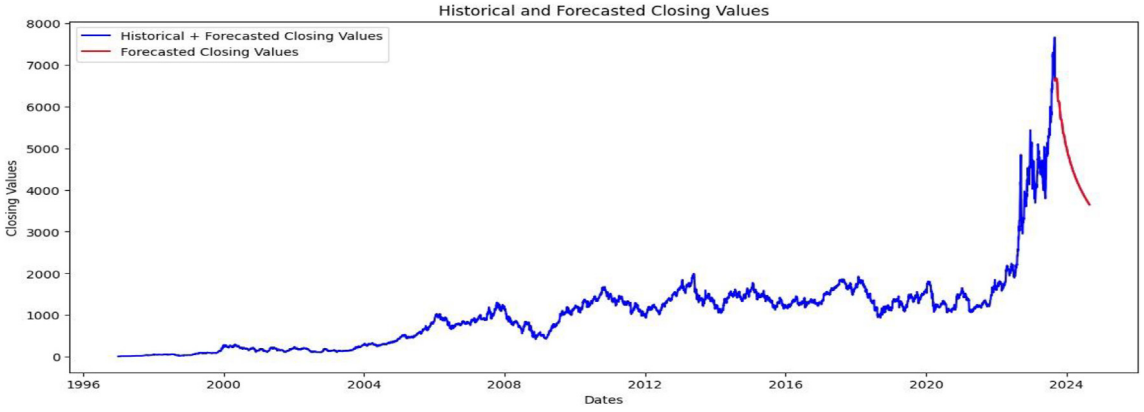


Fig. 9. One year forecast Figure Created by training 20% test data with CNN model.

model (see Fig. 9). The MAPE of the model is 7.60% and the R-Square statistic is $R^2 = 0.95$. After verifying the reliability of the parameters, the model was estimated.

The CNN model predicts that the index will lose value one year after the learning period. The MAPE parameter of the model confirms that the forecasting model has a high degree of accuracy. This is also supported by the R-Square parameter.

The MAPE and R-Square parameters of the estimated ARIMA, FPM and CNN models are presented in Table 2. The table also includes the estimation model for the pre-trend period identified in the ARIMA model.

In general, when the MAPE and R-Square parameters of ARIMA, FPM and CNN models are compared, it is seen in Table 2 that the CNN model has the lowest MAPE and the highest R-Square value. Although the ARIMA model has a higher MAPE value than the FPM, the R-Squared values indicate that the FPM provides better prediction results than the ARIMA model. Therefore, the CNN model is selected as the method that best explains the BIST Banks Index.[5]

Table 2
MAPE and R-Square values of the models.

	MAPE	R-Square
ARIMA (1,0,1)	25%	0,30
ARIMA (1,0,1)[a]	26,0%	0,62
FPM	34,4%	0,82
CNN	7,6%	0,95

[a] Modeling for the period before July 05, 2022 when the trend change is detected.

6. Conclusion and policy implications

In this study, price forecasting models of the BIST Banks Index, which is the representative of the banking system in the capital markets, are estimated, using daily closing data of the BIST Banks Index from Dec 27, 1996, to August 31, 2023. The traditional ARIMA model and two artificial intelligence-based deep learning models (FPM and CNNM) are employed. Our study extends the earlier research by Gunduz et al. (2017) who forecasted BIST 100 stocks using CNN models and Logistic Regression. However, this study is the initial research on the prediction of the BIST Banks Index based on recently developed artificial intelligence models. The findings show that the FPM and CNNM perform better for

[5] Although the basis of the CNN-Corr classifier model used by Gunduz et al. (2017) appears the same as the CNN model used in my study, its application seems different because they utilized software-based models, and the findings may therefore vary according to the employed software codes. As a result, it is difficult to directly compare my results to those of Gunduz et al. (2017).

predicting the BIST Banks Index than the traditional ARIMA model. When the artificial intelligence-based deep learning model forecasts are compared within themselves, the CNNM makes better forecasts than the FPM.

The results have important implications for researchers, investment managers, investors, and policymakers. First, the findings show that the artificial intelligence-based deep learning model forecasts perform better than traditional models. Hence, future studies should employ these models more frequently for the better prediction of asset prices or other financial instrument prices. Second, researchers are advised to use alternative artificial intelligence-based deep learning models as our findings show that the CNNM performs better than FPM model. In terms of implications of the findings for investors and policymakers, the artificial intelligence-based deep learning models can be used to predict future bank index movements in the Turkish banking system, which is critical for the national capital market stability and hence for sustainable economic growth. Third, our results have implications for market efficiency. Our results support the predictability of the index parallel to the efficient market hypothesis' detractors that think equities can fluctuate from their fair market prices and that it is feasible to outperform the market.

Our findings have broader implications for other economies with a significant banking sector share in national capital markets. For example, similar forecasting models can be useful for overseas investors and policymakers as well. Finally, our findings have implications for portfolio diversification for domestic and international investors. Successful prediction of the BIST Banks Index with the artificial intelligence models provides useful information for investors to balance their portfolios to seek maximum returns.

This study is not without limitations. All the models in the study are estimated by using Python programme. However, the predictions of the artificial intelligence-based FPM and CNNM can take a long time depending on the learning time, testing time and time interval used in the models, and the program requires a good computer hardware space due to large amount of data. Therefore, repeating the study under better conditions with more models and a much wider time interval will improve the analysis. This can be achieved in future research and our results in this study can represent a yardstick for future studies' findings.

As this study focused on model comparison based on a single banking index, models using different sector and aggregate indices may perform differently. In addition, we have used only two artificial intelligence models and applied it to an emerging market. Future research utilizing alternative indices, more recently developed artificial intelligence models and higher frequency data from several other emerging and advanced markets can be useful to determine whether the findings in this study from the Turkish banking stock index can be generalized to other indices and markets.

Conflict of interest

There is no conflict of interest.

References

Angadi, M., & Kulkarni, A. P. (2015). Time series data analysis for stock market prediction using data mining techniques with R. *International Journal of Advanced Research in Computer Science, 6*(6), 104–108.

Banerjee, D. (2014). Forecasting of Indian stock market using the time-series ARIMA model. In *2014 2nd international conference on business and information management (ICBIM)* (pp. 131–135). IEEE.

Banking Regulation and Supervision Agency. (2023). *Data, Turkish banking system*.

Borsa Istanbul. (2023). *Indices, BIST stock indices*. https://www.borsaistanbul.com/en/index/1/stock-indices.

Borneklint, N. (2021). *Forecasting prices of Bitcoin and Google stock with ARIMA vs Facebook Prophet. Master thesis*. Sweden: University West.

Box, G. E. P., & Jenkins, G. M. (1976). *Time series analysis forecasting and control* (Revised Edition). California: Holden Day Inc.

Box, G. E. P., & Pierce, D. A. (1970). Distribution of the residual autocorrelations in autoregressive ıntegrated moving average models. *Journal of the American Statistical Association, 65*, 1509–1526.

Caliskan, H., Cevik, E. I., Kirci Cevik, N., & Dibooglu, S. (2021). Identifying systemically important financial institutions in Turkey. *Research in International Business and Finance, 56*, 101374.

Fama, E. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance, 25*, 383–417.

Fang, W., Lan, P., Lin, W., Chang, H., Chang, H., & Wang, Y. (2019). *Combine Facebook Prophet and LSTM with BPNN forecasting financial markets: The morgan taiwan index, 2019 international Symposium on intelligent signal Processing and communication systems (ISPACS), taiwan*.

Garlapati, A., Krishna, D. R., Garlapati, K., Rahul, U., & Narayanan, G. (2021). Stock price prediction using Facebook Prophet and arima models. In *6th international conference for convergence in technology (I2CT)* (pp. 1–7). IEEE.

Gujarati, D. N. (1995). *Basic econometrics* (3rd. Edition). USA: MC-Graw-Hill Inc.

Güleryüz, D., & Özden, E. (2020). The prediction of brent crude oil trend using LSTM and Facebook Prophet. *European Journal of Science and Technology*, (20), 1–9.

Gündüz, H., Yaslan, Y., & Cataltepe, Z. (2017). Intraday prediction of Borsa Istanbul using convolutional neural networks and feature correlations. *Knowledge-Based Systems, 137*.

Hallerbach, W. G. (1994). Index tracking: Some techniques and results. In L. Peccati, & M. Virén (Eds.), *Financial modelling. Contributions to management science*. Physica-Verlag HD. https://doi.org/10.1007/978-3-642-86706-4_7.

Indolia, S., Goswami, A. K., Mishra, S. P., & Asopa, P. (2018). Conceptual understanding of convolutional neural network- A deep learning approach. *Procedia Computer Science, 132*, 679–688.

Jackson, C., Jayachandran, P., Md, A., & V, S. (2021). Stock market analysis and prediction using time series analysis. *Materials Today: Proceedings*. https://doi.org/10.1016/j.matpr.2020.11.364

Kaderli, Y., Petek, A., Doğaner, M., & ve Babayiğit, G. (2013). Measuring the sensitivity of sector indices in Borsa Istanbul to the market index and unsystematic risks. *Anadolu University Journal of Social Sciences, 13*(3), 55–64.

Kartal, M. T. (2018). The importance of banks in the financial sector. In *book: Financial economics* (pp. 5–27). Publisher: Orion Publishing.

Lecun, Y., Bottou, L., Bengio, Y., & Haffner, P. (1998). Gradientbased learning applied to document recognition. *Proceedings of the IEEE, 86*(11), 2278–2324.

Li, J. (2021). Research on market stock index prediction based on network security and deep learning. *Security and Communication Networks*, 1–8. Article ID 5522375.

Malkiel, B. G. (2003). *Princeton university. The efficient market hypothesis and its critics*. CEPS Working Paper No. 91 https://www.princeton.edu/~ceps/workingpapers/91malkiel.pdf.

Newbold, P., Carlson, W. L., & Thorne, B. M. (2003). *Statistics for business and economics*. Upper Saddle River, N.J: Pearson Education Inc. (Prentice Hall).

Oncu, E. (2021). *Forecasting non-fungible token market volume: Facebook Prophet analysis* (pp. 542–548). AL Farabi 10th International Conference on Social Sciences.

Partovi, E., & Matousek, R. (2019). Bank efficiency and non-performing loans: Evidence from Turkey. In J. A. Shumpeter (Ed.), *Vol. 48. Research in international business and finance* (pp. 287–309). The Theory Economic Development, Harvard University Press, 1934.

Public Disclosure Platform. BIST Companies, Indices. https://www.kap.org.tr/en/Endeksler.

Schumpeter, J. A. (1934). *The Theory of Economic Development*. Cambridge MA: Harvard University Press.

Sharma, K., Bhalla, R., & Ganesan, G. (2022). Time series forecasting using FB-Prophet. In *ACM 2022- algorithms, computing and mathematics conference* (Chennai, India).

Smith, J., & Johnson, J. (2020). Forecast evaluation with mean Absolute percentage error (MAPE) method. *Journal of Advanced Methods in Data Analysis and Forecasting, 25*(3), 345–436.

Taylor, S. J., & Letham, B. (2017a). Prophet: Forecasting at scale. *Peer J Preprints, 5*, Article e3190v2. https://doi.org/10.7287/peerj.preprints.3190v2

Taylor, S. C., & Letham, B. (2017b). Prophet: Forecasting at scale. *Meta Research*. https://research.facebook.com/blog/2017/02/prophet-forecasting-at-scale/.

Taylor, S. J., & Letham, B. (2018). Forecasting at scale. *The American Statistician, 72*(1), 37–45.

The Banks Association of Turkiye, Banks and banking sector information, statistics and data query, statistical reports. https://www.tbb.org.tr/en/banks-and-banking-sector-information/statistics-and-data-query/statistical-reports/20.

The World Bank, Turkiye, overview, economic indicator. https://data.worldbank.org/country/turkiye.

The Turkish Capital Markets Association. (2023). *Useful Links & Statistics*. https://icsa.global/statistics.

Toharudin, T., Pontoh, R. S., Caraka, R. E., Zahroh, S., Lee, Y., & Chen, R. C. (2020). Employing long short-term memory and Facebook Prophet model in air temperature forecasting. *Communications in Statistics - Simulation and Computation*, 1–24.

Topaloğlu, E. E., & Karakozak, Ö. (2018). Macroeconomic factors and stock returns: A panel data analysis on BIST bank index firms. *Journal of Accounting and Finance*, (78), 199–216.

Upadhayula, A., Ravilla, A., Varadarajan, I., Viswanathan, S., & Anastasiu, D. C. (2019). Study area recommendation via network log analytics. In *7th IEEE international conference on mobile cloud computing, services, and engineering (mobile cloud)* (pp. 48–55). Newark, CA, USA.

Usher, J., & Dondio, P. (2020). BREXIT election: Forecasting a conservative party victory through the pound using ARIMA and facebook's Prophet. In *Proceedings of the 10th international conference on web intelligence* (pp. 123–128). Mining and Semantics.

Yang, Q., & Wang, C. (2019). A study on forecast of global stock indices based on deep LSTM neural network. *Statistical Research, 36*(6), 65–77.

Yusof, U. K., Khalid, M. N. A., Hussain, A., & Shamsudin, H. (2021). Financial time series forecasting using Prophet. In *book: Innovative systems for intelligent health informatics, data science, health informatics, intelligent systems, smart computing* (pp. 485–495). Springer International Publishing.