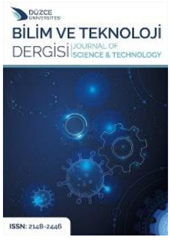

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Review Paper

Time Series Forecasting of MSCI Indices With Machine Learning[1]

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ABSTRACT

Machine learning has become an increasingly important tool for understanding the dynamic nature of financial markets and predicting future price movements. The aim of this study is to determine the most successful forecasting model by comparing the forecasts made by ARIMA, XGBoost, LSTM and Prophet methods using the 15-year daily data of MSCI Turkey and MSCI Germany Indices between 29.03.2009 and 28.03.2024. Root Mean Square Error (RMSE) value is taken as a benchmark to evaluate the model's success. The analyses were conducted using the Python JupyterNotebook program and assumed that all other variables are constant. According to the results, the XGBoost method was found to be the most successful model for the MSCI Turkey Index, while the LSTM model gave the best results for the MSCI Germany Index. These findings suggest that machine learning methods outperform classical forecasting techniques. This study reveals that machine learning is a powerful tool for making more accurate forecasts in financial markets, and that these methods provide more efficient results compared to classical models.

Keywords: *Machine Learning, ARIMA, XGBoost, Prophet, LSTM*

I. INTRODUCTION

Forecasting can be defined as the prediction of future events by analyzing past data. It spans across various fields such as business, industry, economics, environmental science, and finance (Selvin et al., 2017). Time series forecasting, a crucial area within forecasting, involves collecting and analyzing past observations of the same variable to develop a model that explains the underlying relationship. The model is then used to forecast future values of the time series (Zhang, 2023). In addition to traditional forecasting methods, Machine Learning techniques have gained prominence in the literature. Machine learning, in particular, has become a vital forecasting, model selection, and prediction tool for applied researchers in the fields of Economics and Finance (Masini et al., 2023). According to Lawrence (1997), one of the key motivations for predicting stock prices is the pursuit of financial gain. A system that can consistently identify winners and losers in a dynamic market maximizes the utility of the participant who dominates and anticipates the system. As a result, investors continuously seek to dominate this superior system that promises high returns. Additionally, with advancements in technology, the advent of faster computers, the vast information available over the internet, and easy access to this data, stock markets have become more accessible, attracting not only strategic investors but also a large number of non-professional participants.

[1] This study is the extended and final version presented at the International Congress of Business Econometrics and Statistics (icobes2024) organized by Ardahan University between May 29 and June 1, 2024.

The significant impact of the internet on stock markets, coupled with the possibility of obtaining information from primary sources, has made the extraction and use of information in decision-making a critical task (Yoo et al., 2005).

MSCI Indices, managed by Morgan Stanley Capital International (MSCI), offer a global financial services platform that provides a broad view of the economic condition of countries and the overall health of stock markets. The MSCI indices, which include the largest publicly traded companies by market value and liquidity, offer valuable insights into market trends. For example, the MSCI Germany Index covers the large and mid-cap segments of the German market, representing approximately 85% of the stock universe in Germany. Similarly, the MSCI Türkiye Index serves as an important indicator for the Turkish economy, widely used by both local and foreign traders.

Stock price forecasting is considered one of the most challenging areas in financial forecasting due to the complex structure of the stock market. Many investors aim to identify and utilize forecasting methods that can guarantee easy profits while minimizing risks in stock market investments. This desire continues to motivate researchers to develop new prediction models. Time series modeling has historically been a significant area of academic research, guiding researchers in fields such as biology, health, finance, and many other disciplines during forecasting processes. LSTM models, due to their ability to recall historical data, are seen as powerful tools for forecasting in volatile markets (Hochreiter & Schmidhuber, 1997). The Prophet method, developed by Facebook, is well known for its ability to analyze seasonality and trends effectively, making it successful in capturing long-term trends and widely used for forecasting economic indicators (Taylor & Letham, 2018; Alim et al., 2020). Alongside traditional methods, Machine Learning techniques are proposed as alternatives to statistical methods for time series prediction in the literature. However, more applications and evidence are needed regarding the accuracy and reliability of these methods. Motivated by this, this study aims to determine the most successful forecasting model by comparing the ARIMA, XGBoost, LSTM, and Prophet methods using 15 years of daily data from the MSCI Türkiye and MSCI Germany Indices, spanning from March 29, 2009, to March 28, 2024.

This study emphasizes the development of time series forecasting in financial markets and aims to make a significant contribution, especially with the forecasts made on MSCI Turkey and MSCI Germany Indices. With the developing technology and increasing data access, the limitations of traditional forecasting methods are being overcome, and there is the availability of more powerful and flexible models such as machine learning. In this context, the possibilities of meeting the forecasts made in modern ways such as ARIMA, XGBoost, LSTM and Prophet are provided for the analysis of financial markets in a more accurate and reliable way. The study can show that machine learning methods can exhibit superior performance compared to their classical methods and provides a new perspective for this comprehensive research. In addition, the success of the forecasts of MSCI Turkey and MSCI Germany Indices once again enables the creation of more reliable models in financial analyses that will allow investors to make more precise forecasts in decision-making data. This study reveals how valuable a tool machine learning is in terms of financial forecasting and economic analyses, while also making a significant contribution to the field. The increase in the replication of models to make transferable and accurate predictions of uncertainty and volatility in financial markets offers the opportunity to test the modification of current methods of econometric systems and engineering finance. The study particularly encourages the integration of machine learning in the analysis of financial markets and shows that such techniques constitute an effective basis for detailed physical studies. In this context, the findings obtained both contribute to the academic literature and have great potential with a flexible perspective of investment options.

II. LITERATURE REVIEW

There are important studies in the academic literature that address the methodological contributions of machine learning methods in time series forecasting. For this purpose, one of the studies in the literature that can be supported methodologically is Selvin et al. (2017) aimed to compare the performance of RNN, LSTM and CNN methods in price prediction of companies operating in NSE. As a result of the analyzes conducted for this purpose, it was observed that the CNN model exhibited higher performance. In the same direction, İlkçar (2023) used R-squared, MSE, RMSE and MAE values as criteria in his study aiming to compare the success performance of FNN, LSTM and GRU machine learning models in predicting the future prices of THY shares. As a result of the analysis, it was determined that GRU and LSTM models showed 99% success. Ustalı Koç et al. (2021) used Artificial Neural Networks (ANN), Random Forest (RF) algorithm and XGBoost algorithm methods in their study aiming to predict the future prices of companies listed in the BIST 30 Index. The findings show that the XGBoost algorithm gives better results than other algorithms. From another perspective, Satrio et al. (2021) aimed to use a Machine Learning model to predict the trend of the disease in Indonesia as well as to find the forecast of when normality will return after Covid-19. The empirical study using the Facebook-supported Prophet Forecasting Model and ARIMA Forecasting Models concludes that Prophet generally outperforms ARIMA. Sharma and Jain (2023) aim to test the best performing model for future price prediction of Apple stock with KNN, Ada Boost, SVM, RF and XGBoost methods. Analyses based on MSE values show that the XGBoost method is effective in generating future stock prices.

In a study by Yurttabir and Sen (2021), the effectiveness of the Prophet model in predicting financial performance in the manufacturing sector was evaluated. It is emphasized that Prophet is particularly successful in capturing trend and cyclical fluctuations, but has some limitations in short-term forecasting. The study highlights the importance of data preprocessing techniques and hyperparameter optimization to improve the usability of the Prophet model in financial forecasting processes. Gajamannage et al. (2023) evaluate the performance of sequentially trained LSTM models for real-time forecasting in equity, cryptocurrency and commodity markets. The findings show that LSTM models are more successful in volatile markets and outperform models such as ARIMA and Prophet in short-term forecasting, especially by handling complex financial data.

Paliari et al. (2021) This study compares the performance of LSTM, XGBoost and ARIMA models in time series forecasting. The results show that LSTM and XGBoost provide better forecasting results than ARIMA, especially when the data values show a wide range. Similarly, Gifty and Li (2024) evaluate the performance of LSTM, ARIMA and XGBoost algorithms in forecasting stock prices. The study reveals that the XGBoost model performs strongly with high R-squared value and low error metrics.

Abdullah et al. (2024) This study aims to predict stock prices using text analysis and deep learning approaches. In addition, the explainability of the models used is emphasized, and it is aimed to make the forecasting processes understandable. In this context, the World Halal Tourism Composite Sentiment Index (WHTCSI) is constructed to predict stock prices for the halal tourism sector. The findings revealed that Convolutional Neural Networks (CNN) outperformed all other models. The results were also consistent when country-level data were taken into account.

Shaban et al. (2024) In this paper, a new system based on deep learning (SMP-DL) for stock market price prediction is proposed. This system consists of two stages: (i) data preprocessing (DP) and (ii) stock price prediction (SP2). In the first stage, the data is cleaned by detecting and eliminating missing values, feature selection and data normalization. In the second stage, the cleaned data are processed through the forecasting model. In the SP2 process, long-short-term memory (LSTM) and bidirectional gated iterative unit (BiGRU) models are combined to predict stock closing prices. The results show that the proposed system performs well compared to existing methods.

Jabed (2024) argues that forecasting stock market prices is a challenging task in the financial sector. In the study, it was revealed that advanced machine learning models can predict stock price movements with a certain level of accuracy when the correct parameter settings and appropriate forecasting models are developed. In this context, the long-short-term memory (LSTM) model classified as recurrent neural networks (RNN), the Facebook Prophet algorithm for time series forecasting, and the Random Forest Regression model were used to predict the stock prices of 10 Dhaka Stock Exchange (DSEbd) listed companies and six international large-scale companies. The datasets for local companies are obtained from the graphical representations of the DSEbd website, while the data for international companies are obtained from Yahoo Finance. The Facebook Prophet model was found to be reasonably accurate in long-term forecasting, taking into account daily, weekly and annual seasonality and holiday effects to analyze market trends.

Li (2025) The study examines the applicability of machine learning algorithms in forecasting stock prices during crisis periods. It is stated that models such as Random Forest, Support Vector Machines, Linear Regression, Convolutional Neural Networks, Artificial Neural Networks and Long-Short Term Memory Networks are widely used during periods of high market volatility. It is observed that these models improve forecasting accuracy by integrating policy and news indicators that reflect social changes and investor sentiment. In addition, some models have been reported to further improve forecasting performance by applying hyperparameter optimization methods. However, it is revealed that existing machine learning models face problems such as low interpretability, limited applicability and high sensitivity to external factors. This leads to a decrease in investor confidence, an increase in training costs, and inconsistent results across different stocks and special periods.

Beniwal et al. (2024) This study comprehensively examines the capacity of deep learning models to predict long-term, up to one year, daily prices of global stock indices out-of-sample. The performance of six models such as Deep Neural Network (DNN), Recurrent Neural Network (RNN), Long-Short Term Memory (LSTM), Bidirectional Long-Short Term Memory (Bi-LSTM), Closed Recurrent Unit (GRU) and Convolutional Neural Network (CNN) is compared using Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). The models predict the long-term daily prices of five global stock indices, such as Nifty, Dow Jones Industrial Average (DJIA), DAX Performance Index (DAX), Nikkei 225 (NI225) and Shanghai Stock Exchange Index (SSE). The results confirm that the LSTM model is superior in forecasting long-term daily prices. While Bi-LSTM does not improve the results of LSTM, it outperforms the other algorithms.

Singh and Praveen (2025) discuss the difficulty of predicting stock market values with any accuracy due to the complexity and volatility of financial markets. Although many approaches have been applied, including technical and fundamental analysis, no method can offer perfect accuracy. However, other techniques, such as deep learning and machine learning algorithms trained based on historical data, can produce more realistic and accurate projections within given confidence intervals. In this study, in order to verify the accuracy of various regression algorithms, they were compared using R2 scores and RMSE values. According to the findings, it was found that linear regression provides superior accuracy and outperforms other methods in metrics such as R2 and RMSE.

The content of the research conducted in this direction includes the data set and methodology section. This section provides information about the Indices included in the analysis and the methodology. Then, the findings obtained from these methods were presented in tables, interpreted and analyzed. In addition, by comparing the RMSE values obtained, the most successful model in price prediction within the constraints was determined. Finally, in the conclusion section, a general evaluation of the study was made and suggestions for future studies were presented after the discussion.

III. DATASET AND METHODOLOGY

The study aims to identify the most successful model for the MSCI Türkiye and MSCI Germany indices through ARIMA, XGBoost, LSTM and Prophet methods. For this purpose, the 15-year daily closing data of the indices included in the analysis between 29.03.2009 and 28.03.2024 were obtained through Yahoo Finance. The indices and index codes included in the analysis are presented in Table 1.

Table 1. Indices and Index codes included in the analysis

Index	Index Code
MSCI Türkiye Index	TUR
MSCI Almanya Index	EWG

Below are figures showing the closing prices of the MSCI Türkiye and MSCI Germany indices. These figures visualize the performance and fluctuations of these indices over the years.

Figure 1. MCSI Türkiye Index Closing Prices

Figure 1 shows the closing prices of the MSCI Türkiye Index. While there was a strong uptrend between 2010 and 2014, a fluctuating and relatively low-level movement was observed after 2018.

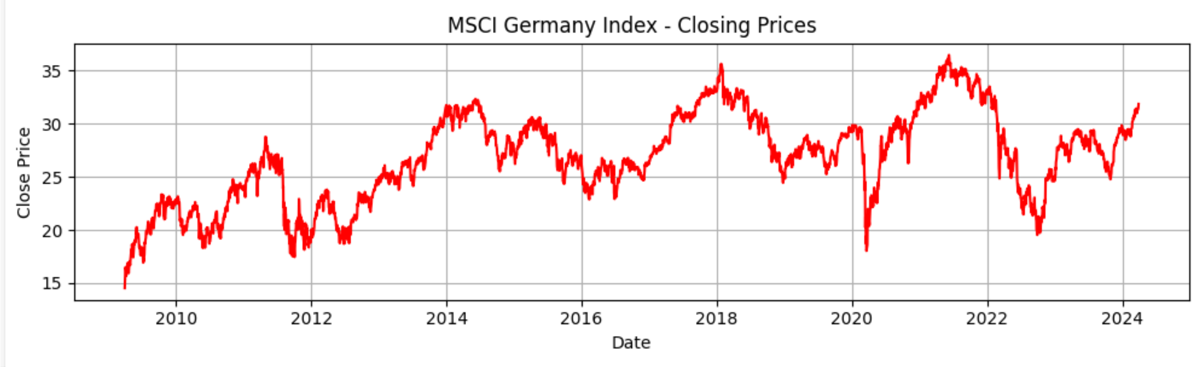

Figure 2: MCSI Germany Index Closing Prices

Figure 2 shows the closing prices of the MSCI Germany Index. Although it has generally been on an upward trend since 2010, sharp fluctuations and sharp declines after 2018 are noteworthy.

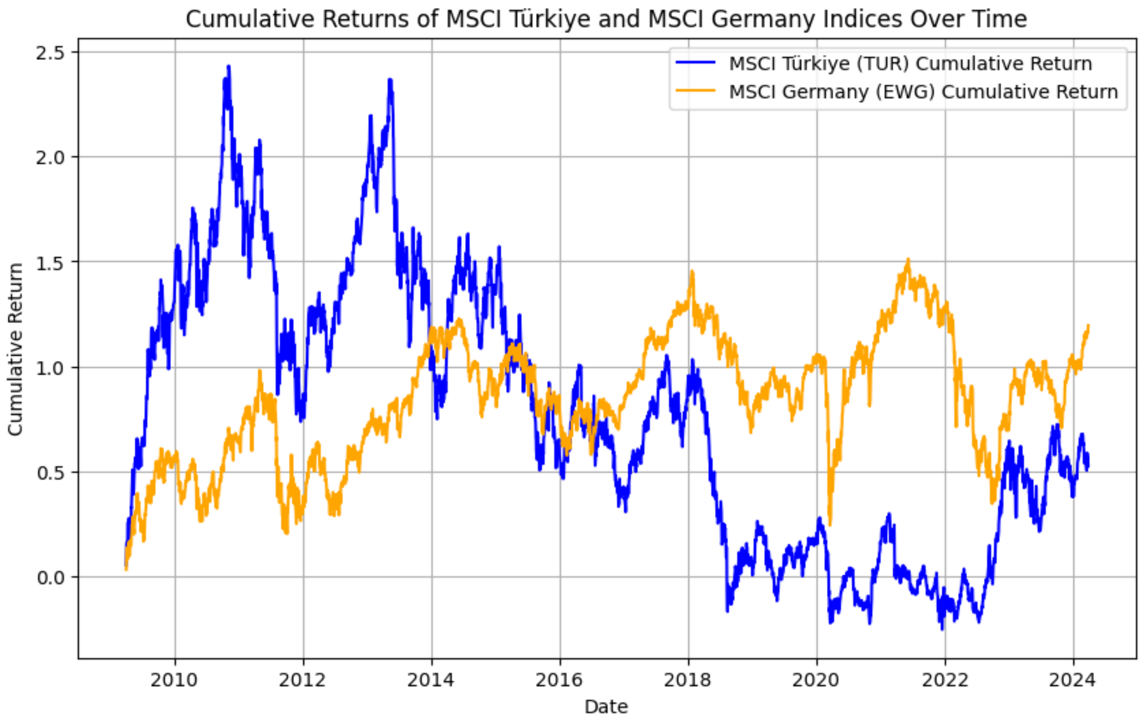

Figure 3: Cumulative Returns of MSCI Türkiye and MSCI Germany Indices Over Time

Figure 3 compares the cumulative returns of the MSCI Türkiye (TUR) and MSCI Germany (EWG) indices over time. Between 2010 and 2013, the MSCI Türkiye index experienced significant growth but exhibited high volatility after 2013, following a fluctuating pattern. A notable downward trend was observed after 2018, and despite attempts at recovery post-2020, it has not reached its previous levels. In contrast, the MSCI Germany index showed a more stable upward trend, reaching a similar level to the MSCI Türkiye index around 2016. However, after 2018, it performed relatively better. Despite a decline in 2022, it regained momentum during the 2023-2024 period. The primary difference between this graph and the previously created closing price figures lies in how returns are represented. While closing price figures illustrate price movements over time, the cumulative return graph provides a clearer perspective on investment performance. It shows how an investment has gained or lost value from a given starting point, rather than just displaying absolute price changes. This allows for a better interpretation of an investor's profit or loss over time.

Within the framework of the methodological approaches mentioned in the previous section, the Python Jupyter Notebook application was used in the study to forecast the prices of selected MSCI Indices. For both indices considered in line with the applications, 70% training and 30% test groups were formed and analyzed.

In the study, the unit root test is first applied for each index and then the optimal ARIMA model is determined. SARIMA seasonality test is performed with the specified ARIMA model and the RMSE value is extracted from the ARIMA model. Finally, the optimal parameters for XGBoost, LSTM and Prophet methods are determined and the RMSE value is found. The model with the lowest RMSE value is considered to be the most successful model among the selected models. For the purpose of the study, ARIMA, XGBoost, LSTM and Prophet models are analyzed with the Pyhton program by taking the daily closing prices of the indices and the methodology for all models is presented in the section.

The MSE reflects how much the expected value of the estimator is systematically different from the true value, as well as the variance, which measures how much the predicted value varies from the expected value or its mean (Schluchter, 2025). The RMSE value is the square root of the MSE value and is expressed as follows.

$$\text{RMSE}=\sqrt{\frac{1}{n}\sum_{t=1}^{n} (y_t - \hat{y}_t)^2} \tag{1}$$

A. ARIMA (p, d, q) Model

The ARIMA (p, d, q) model is a linear model suitable for stochastic series. In general, it stems from the autoregressive model AR (p), the moving average model MA (q) and the combination of AR (p) and MA (q), the ARMA (p, q) model (Chen et al., 2008). The ARIMA (p, d, q) model is expressed by the equation shown below:

$$y_t = a + \emptyset_1 Y_{t-1} + \cdots + \emptyset_p Y_{t-p} + \emptyset_i \varepsilon_{t-1} + \cdots + \emptyset_q \varepsilon_{t-q} + \varepsilon_q \tag{2}$$

where α is the constant term (i.e., the mean of the underlying stochastic process), φi is the i-th autoregressive parameter, φj is the j-th moving average parameter, ε_t is the error term at time t, and yt is the observed value at time t (Singh & Praveen, 2025).

The ARIMA model can be explained with this formula as a general approach. To define the ARIMA model, the Bayesian Information Criterion (BIC) is used with several rules and least squares optimizes the parameters as described by Box and Jenkins (1976). The biggest advantage of this applied method is its extreme speed, so it can produce alternative ARIMA models very quickly (Goodrich, 2000). The flow diagram of the ARIMA model used in the study is shown in Figure 4.

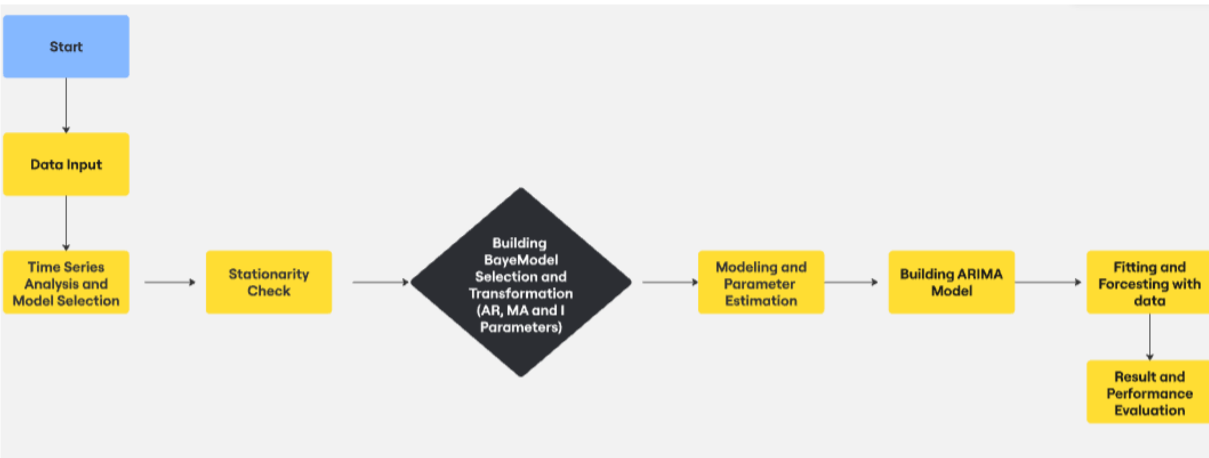

Figure 4. ARIMA model flow diagram

B. LSTM Model

Hochreiter and Schmidhuber (1997) designed a new recurrent network architecture, long short-term memory (LSTM), with a gradient-based learning algorithm.
LSTM is a modified version of RNN (Recurrent Neural Network). The RNN is known as the most suitable method for stock price forecasting as it can analyze time series patterns and is expressed by the following formula (Bathla, 2020):

$$c_t = F_t * c_{t-1} + l_t * \overline{c_t} \tag{3}$$

Where c t is the current cell state and ct-1 is the previous cell state. Ft is the forgotten state and It is the input state.

An LSTM has three gates: an input gate that determines whether new input is let in, a forget gate that deletes unimportant information, and an output gate that decides what information to output. These three gates are analog gates based on the sigmoid function operating in the range 0 to 1. LSTM models work efficiently and are widely used in various tasks. The activation function in the output layer determines which direction the training will take here (Yadav et al., 2020; Albeladi et al., 2023). The flow diagram of the LSTM model used in the study is shown in Figure 5.

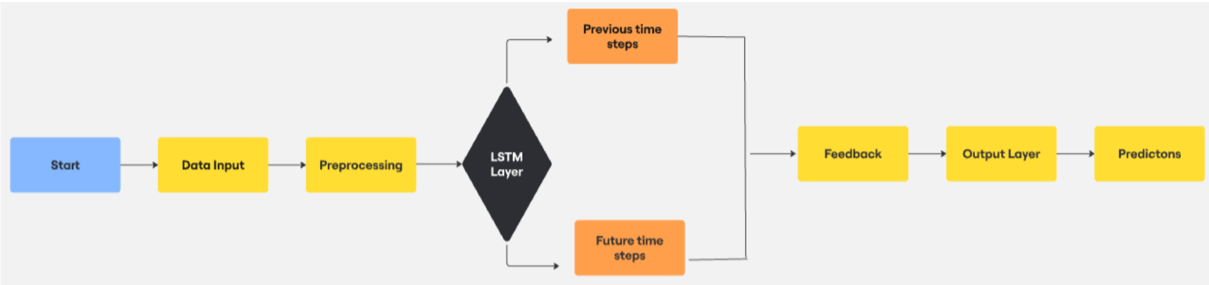

Figure 5. LSTM model flow diagram

First, data entry is performed. After the data is prepared with pre-processing steps (such as normalization, removing trend and seasonality components in time series data), the input data to the LSTM layer and the hidden states from previous time steps are processed. LSTM makes predictions in future time steps by storing information from previous time steps. In this way, it is possible to model temporal dependencies in time series. LSTM network is trained using the feedback method. By using the error (loss) function, the weights are updated and the prediction ability of the network is improved. It then takes the output of the LSTM layer and usually makes a prediction or classification. Once the model is trained or the prediction is made, the process ends.

C. XGBoost Model

The XGBoost model is a gradient-assisted decision tree machine learning algorithm that uses a regression tree as an internal decision tree. Stepwise Boosting is a method that involves developing new models that predict the residuals or errors of old models, which are then combined to provide the final prediction (Sharma & Jai, 2023). The equation for the model is as follows:

$$L_k = \sum_{j=1}^{N}(y_{t+j} - \hat{y}_{t+j})^2 + \sum_{k=1}^{K}(\gamma T + \frac{1}{2} a \sum_{m=1}^{T} \omega_m^2) \tag{4}$$

Where T is the number of leaf nodes, N is the set of all instances in leafm, ω is the score of the leaf mismeasured bym, α andy are the parameters of the tree (Oukhouya et al., 2024).

The main purpose of boosting machine-generated models is to combine multiple predictive models with low levels of accuracy into a model with high reliability. A certain number of models need to be combined in order to be estimated with appropriate parameter settings. Depending on the data set size, the model may need to be repeated thousands of times or more to achieve a high level of accuracy. It is claimed that the XGBoost model can solve this problem better. This model XGBoost was first proposed by Chen Tianqi and Carlos Gestrin in 2011 and has been continuously optimized and perfected through numerous studies in the following stages. (Li et al., 2019; Alim et al., 2020).
In this direction, the flow diagram of the XGBoost model used in the study is shown in Figure 6.

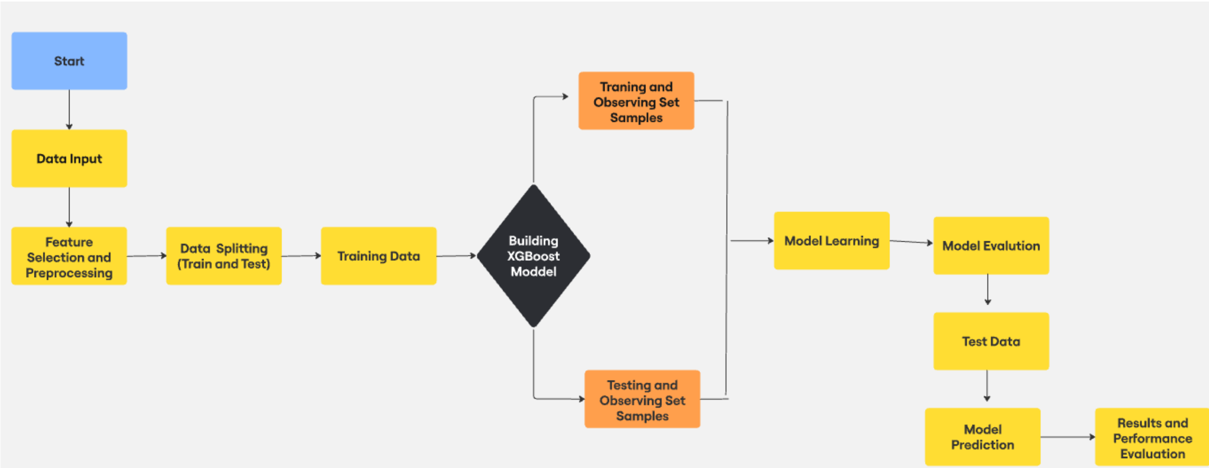

Figure 6. XGBoost model flow diagram

Figure 6 can be summarized as follows. Firstly, data entry is performed. Preliminary operations such as necessary feature selection, missing data processing, and normalization are performed on the data set. The data set is usually divided into two parts: training and testing set. While the training set is used to train the model, the test set is used to evaluate the performance of the model. The XGBoost model learns by taking samples from training data. Weak learners are strengthened using the boosting algorithm. The XGBoost model is created based on the training data. In this process, tree structures are brought together to create a powerful estimator. XGBoost learns each tree structure by taking examples from the training and observation sets. After the training process is completed, the model's performance is usually evaluated on test data. This step shows how well the model generalizes and its predictive power. Predictions are made using the XGBoost model trained on test data. These predictions can often be values or classes of the target variable. Predictions produced by the model are evaluated with performance metrics by comparing them with actual values.

D. Prophet Model

Prophet, created by Facebook's Core Data Science team and proposed by Taylor and Letham (2018), is designed to be automated in nature, allowing for greater ease of use in tuning time series methods, while also having heuristic parameters that can be adjusted without knowing the details of the underlying model. The model is formulated as follows Taylor and Letham (2018):

$$y(t) = g(t) + s(t) + h(t) + \varepsilon_t \quad (5)$$

Here, $g(t)$ is the trend function that models non-periodic variations in the value of the time series, $s(t)$ represents periodic variations (e.g., weekly and annual seasonality), and $h(t)$ represents the effects of holidays occurring on potentially irregular schedules over one or more days.

Aiming to facilitate high quality forecasts, Prophet works best with time series that contain seasonal data and are robust to outliers and changes in trend. Prophet's automated nature lends flexibility to time series data with dramatic changes (Taylor & Lethami, 2018; Yenidoğan et al., 2018). The flow diagram of the XGBoost model used in the study is shown in figure 4.

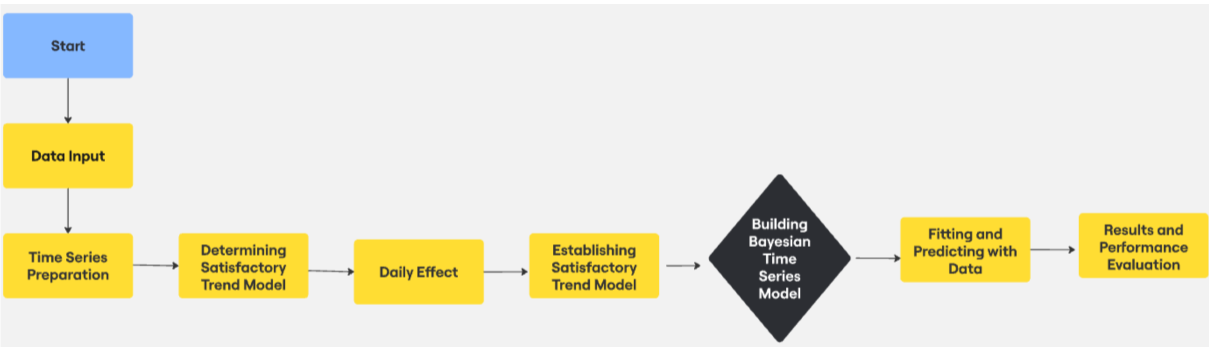

Figure 7. Prophet model flow diagram

After starting the process in Figure 7, it can be seen that the data setting is loaded and the necessary measurements are made. These steps may include handling missing data, converting to data format, and editing if necessary. A satisfactory trend model of the daily time series is determined, which is used to capture regularities and trends over time. Then, the daily, weekly and annual effects observed in the time series are determined. A satisfactory trend model is updated or created with the determined effects. It makes predictions for a certain period of time through the Bayesian time series model, which takes into account changes and uncertainties over time by adapting to the data. It is then trained on daily data and makes predictions, and the daily predictions include future values in the time series. Performance is evaluated by comparing the daily predictions produced by the model with actual data.

Table 2. Advantages and Disadvantages of Forecasting Models Paliari et al. (2021)

	Advantages	Disadvantages
ARIMA	Successful on small data sets, statistically interpretable.	It cannot learn complex data structures and its success may decrease in the long term.
XGBoost	Strong performance on big data sets.	Parameter optimization can be difficult.
LSTM	It can learn long-term relationships, works well in volatile markets.	Training time is long, computational costs are high.
Prophet	Analyzes seasonality and trends well.	Short-term forecasts may be less successful.

Table 2 presents a comparison of the advantages and disadvantages of the ARIMA, XGBoost, LSTM and Prophet methods used in this study. This comparison helps to understand under which conditions each model performs better and under which conditions it has limitations. In particular, LSTM's capacity to learn long-term relationships, XGBoost's strong performance on large data sets and Prophet's ability to analyze seasonality stand out. This analysis provides critical guidance for investors and researchers interested in financial modeling to determine which model is more effective under which market conditions.

IV. ANALYSIS AND FINDINGS

In this section, ARIMA, XGBoost, LSTM and Prophet methods are used to forecast the MSCI Türkiye and MSCI Germany indices using 15-year daily data between 29.03.2009 and 28.03.2024. In order to determine the model that gives the best solution before the results to be obtained by applying these machine learning models, ARIMA test was applied for both indices using Pyhton program. As a result of the ARIMA test conducted for the MSCI Türkiye Index, the most successful model is (2.1.2), while the most successful model for MSCI Germany is (3.1.3). In the light of these results, the results of the empirical analyses conducted with these methods and with a data set of 3775 observations are presented in Table 3 in the perspective of the value that determining the best model will provide to the literature and market participants.

Table 3. *Model Outputs and RMSE Value Results for MSCI Türkiye Index*

	ARIMA RMSE Value	XGBoost RMSE Value	LSTM RMSE Value	Prophet RMSE Value
MSCI Türkiye Index	20.89	0.67	0.95	7.46

Table 4. Model Outputs and RMSE Value Results for MSCI Germany Index

	ARIMA RMSE Value	XGBoost RMSE Value	LSTM RMSE Value	Prophet RMSE Value
MSCI Germany Index	4.61	0.45	0.38	2.59

The RMSE (Root Mean Square Error) values obtained were taken as criteria for determining the most successful model. When the estimation results of ARIMA RMSE value, XGBoost, LSTM and Prophet models are analyzed, the RMSE value of MSCI Türkiye Index is 20.89 and the RMSE value of MSCI Germany Index is 4.61. Immediately afterwards, these indices were modeled with XGBoost, Facebook-powered Prophet and LSTM machine learning methods and the RMSE values obtained for the MSCI Türkiye Index were 0.67, 7.46 and 0.95, respectively, while the RMSE values obtained for the MSCI Germany Index were 0.45, 2.59 and 0.38 respectively. When the findings are evaluated, assuming that all other variables remain constant, the XGBoost method is the most successful model for the MSCI Türkiye Index, while the LSTM Model is the most successful model for the MSCI Germany Index.

Based on the RMSE values obtained from both indices, the graphs of the most optimal models are shown below.

Figure 8. LSTM Forecasting Results for the MSCI Germany Index

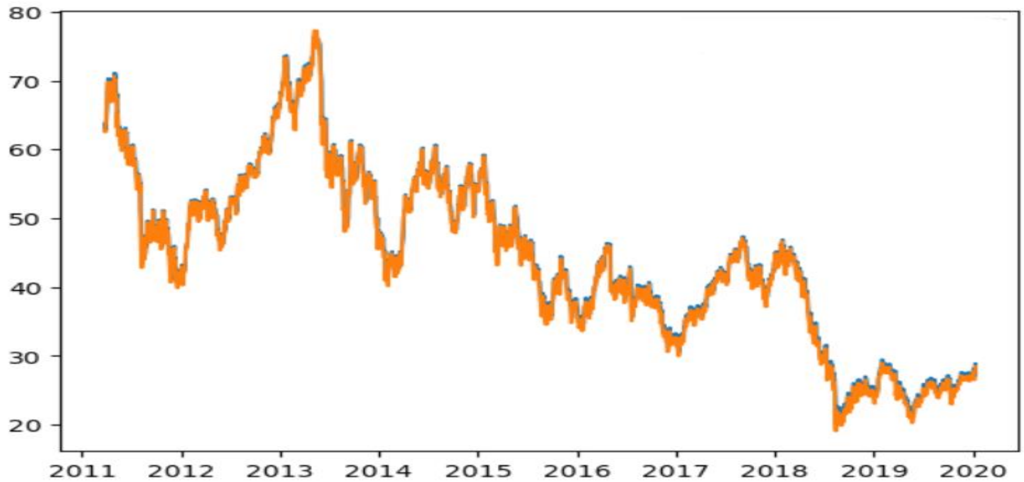

Figure 9. XGBoost Forecasting Results for the MSCI Turkey Index

Figures 8 and Figure 9 show the LSTM model forecast results and closing prices of the MSCI Germany Index and MSCI Türkiye Index, respectively. For both indices, the blue line represents the current closing prices, and the orange line represents the forecast prices. According to the graphical outputs of the LSTM model, it can be claimed that the reliability of the findings and the validity of the model are supported as the current closing price and forecast price curves are very close to each other.

The LSTM model applied to the MSCI Germany Index exhibits a more stable and close fit between the forecast curve and actual values thanks to its ability to capture long-term dependencies in time-series data. This can be attributed to the LSTM's ability to successfully model nonlinear dynamics and trend movements. In contrast, the XGBoost model used on the MSCI Turkey Index is inherently more sensitive to short-term fluctuations, and significant differences between the forecast curve and actual values are observed during periods of high volatility.

V. CONCLUSION

The main purpose of building a time series model is equivalent to building the closest and most accurate model to the values present in the series. From a statistical point of view, time series are defined as random processes that change over time. The most distinctive feature of time series is that the distribution of observations at a given point, depending on the previous value of the series, depends on the results of the previous observations, making the results simply independent (Albeladi et al., 2023).

In the stock market, time series analysis and forecasting are of great importance. Because the primary objective of a business is to maximize the value of the firm and its shareholders. This is possible by selecting the investment instrument that provides the maximum return on investment instruments with the same level of risk or the investment instrument that provides the minimum risk on investment instruments that provide the same level of return. Accurately predicting the future prices of investment instruments holds significant importance for market participants in terms of risk management and strategic decision-making. In this context, the present study concentrates on forecasting practices within capital markets. Specifically, it aims to evaluate and compare the predictive performance of four widely used methods—ARIMA, XGBoost, LSTM, and Prophet—by applying them to 15 years of daily data from the MSCI Turkey and MSCI Germany Indices, covering the period between March 29, 2009, and March 28, 2024. The ultimate objective is to identify the most effective model for forecasting index movements in emerging and developed markets. The RMSE values obtained were taken as the criterion for determining the most successful model. When the findings are evaluated, it is seen that the XGBoost method is the most successful model for the MSCI Türkiye Index, while the LSTM Model is the most successful model for the MSCI Germany Index, assuming that all other variables remain constant.

The fact that XGBoost is the most successful model for the MSCI Türkiye Index may reflect the volatile nature of Turkish markets. This may be advantageous for investors with short-term trading strategies. For the MSCI Germany Index, LSTM was more successful, which may indicate that the German market is more stable. The findings of the study may help investors better understand trends and price fluctuations in MSCI indices. By determining which model is more successful under certain market conditions, more informed investment decisions can be made. In this respect, the results of our study show how machine learning methods can be used to develop investment strategies based on MSCI indices in financial markets.

This study's findings indicate that machine learning methods, particularly XGBoost for the MSCI Türkiye Index and LSTM for the MSCI Germany Index, outperform traditional forecasting techniques such as ARIMA and Prophet in terms of prediction accuracy. By using a 15-year dataset of daily stock prices, this research provides empirical evidence of the effectiveness of machine learning algorithms in forecasting stock indices. The contribution to the literature lies in demonstrating the practical application of machine learning models in financial forecasting, specifically for stock indices. The results challenge traditional approaches and underline the potential of advanced machine learning techniques in improving stock market predictions. This study also offers insights into the performance differences between machine learning methods and traditional models, contributing to the growing body of research exploring new methodologies for financial time series forecasting.

In this respect, the results of MSCI Türkiye Index are similar to Sharma and Jain (2023) and MSCI Germany Index results are similar to İlkçar (2023); Jabed (2024) and Beniwal et al. (2024). Therefore, considering the results, it can be said that machine learning methods perform better than classical methods. In future studies, it is thought that measuring the performance of machine learning methods with different indices and models and comparing them with other traditional models will be of interest to market participants and contribute to the literature.

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