PRICE FORECASTING IN ISLAMIC AND CONVENTIONAL INDICES: HYBRID MODEL PROPOSALS WITH HYPERPARAMETER OPTIMIZATION

İSLAMİ VE GELENEKSEL ENDEKSLERDE FİYAT TAHMİNİ: HİPERPARAMETRE OPTİMİZASYONU İLE HİBRİT MODEL ÖNERİLERİ

Diler TÜRKOĞLU, Fatih KONAK

33

Çukurova Üniversitesi Sosyal Bilimler Enstitüsü Dergisi
Yıl: 2026 Sayfa: 1-15
https://dergipark.org.tr/tr/pub/cusosbil

DOI: 10.35379/cusosbil.1638421

Geliş Received: **03.12.2024**
Kabul Accepted **17.05.2025**

PRICE FORECASTING IN ISLAMIC AND CONVENTIONAL INDICES: HYBRID MODEL PROPOSALS WITH HYPERPARAMETER OPTIMIZATION [1]

İSLAMİ VE GELENEKSEL ENDEKSLERDE FİYAT TAHMİNİ: HİPERPARAMETRE OPTİMİZASYONU İLE HİBRİT MODEL ÖNERİLERİ

Diler TÜRKOĞLU [2] **, Fatih KONAK** [3]

ABSTRACT

Stock price forecasting is a complex, stationary, and nonlinear time series estimation problem influenced by numerous factors. This complexity renders basic models inadequate for producing accurate forecasts of future stock prices.. Thus, precise price forecasting is crucial in this intricate and dynamic market where participants strive to make well-informed decisions to minimize losses and maximize profits. Motivated by this necessity, the present study aims to forecast future prices of selected indices constructed according to both Islamic and traditional criteria and to propose the most effective forecasting model for market participants. . Twelve indices- six traditional and six Islamic- were examined in this context using the ARIMA, XGBoost, LSTM, and Decision Tree methods. The investigation revealed that machine learning models outperformed the conventional approaches in terms of outcomes. The optimal parameters were then acquired and XGBoost-Decision Tree, LSTM-XGBoost, and LSTM-Decision Tree hybrid models were developed based on the results obtained. In this regard, 84 distinct models with seven algorithms- 1 conventional, 3 machine learning, and 3 hybrid models- with optimized hyperparameters were applied to the 12 indices. RMSE values were used to evaluate model performance. The LSTM-Decision Tree model was shown to be the greatest predictor for the BIST Participation 100 Index, while the LSTM-XGBoost model was the best predictor for all other indices.

ÖZ

Hisse senedi fiyat tahmini karmaşık, durağan ve doğrusal olmayan bir zaman serisi tahminidir ve birçok faktörden etkilenmektedir. Bu durum da hisse senetlerinin gelecek fiyat tahminlerinin basit modellerle tahmin edilmesini zorlaştırabilmektedir. Dolayısıyla piyasa katılımcılarının kayıpları en aza indirmek ve karlarını maksimize etmek amacıyla bilinçli karar almaya çalıştıkları bu karmaşık ve dinamik piyasada, fiyatların doğru tahmini büyük önem arz etmektedir. Bu motivasyonla çalışmada İslami ve geleneksel kriterlerle oluşturulmuş seçili endekslerin gelecek fiyatlarının tahmin edilmesi ve en başarılı modelin tespit edilerek piyasa katılımcılarına fiyat tahminlemesi için model önerisi getirilmesi amaçlanmaktadır. Bu kapsamda, çalışmada 6 geleneksel, 6 İslami olmak üzere 12 Endeks ARIMA, XGBoost, LSTM ve Karar Ağacı yöntemleri ile analiz edilmiştir. Analizler neticesinde makine öğrenimi modellerinin gelenekseldendaha üstüm performans gösterdiği tespit edilmiştir. Bu bulgularla elde edilen en iyi parametreler aracılığıyla XGBoost-Karar Ağacı, LSTM- XGBoost ve LSTM-Karar Ağacı hibrit modelleri oluşturulmuştur. Bu doğrultuda optimize edilen hiper parametreler ile 1 geleneksel, 3 makine öğrenimi ve 3 hibrit model olmak üzere 7 algoritma ile 12 Endeks toplamda 84 farklı modelle analiz edilmiştir. Model performansını ölçmek için RMSE değerleri tespit edilmiş ve geliştirilen hibrit modeller kapsamında BİST Katılım 100 Endeksi'nde LSTM-Karar Ağacı; diğer tüm Endekslerde ise LSTM-XGBoost modelinin en iyi tahminci olduğu sonucuna ulaşılmıştır.

Keywords:
Forecasting,
XGBoost,
LSTM,
Decision Tree,
Hybrid model.

Anahtar Kelimeler:
Tahminleme,
XGBoost,
LSTM,
Karar Ağacı,
Hibrit model.

[1] Bu çalışma 09-12 Ekim 2024 tarihleri arasında Nevşehir'de düzenlenen 27. Finans Sempozyumunda yazarlar tarafından sözlü olarak sunulan bildirinin genişletilmiş ve son halidir.

[2] Dr. Öğretim Üyesi, Ardahan Üniversitesi, İktisadi ve İdari Bilimler Fakültesi, dilerturkoglu@ardahan.edu.tr, https://orcid.org/0000-0001-5247-1590

[3] Prof. Dr., Hitit Üniversitesi, İktisadi ve İdari Bilimler Fakültesi, fatihkonak@hitit.edu.tr, https://orcid.org/0000-0002-6917-5082

Alıntılamak için/Cite as: Türkoğlu D. ve Konak F., (2026). Price Forecasting In Islamic And Conventional Indices: Hybrid Model Proposals With Hyperparameter Optimization, Çukurova Üniversitesi Sosyal Bilimler Enstitüsü Dergisi, s. 1-15

INTRODUCTION

One of the most crucial elements of capital markets, stock markets facilitate the dissemination of capital to the general public, the effective and efficient distribution of resources, and the promotion of economic growth. Social and economic growth are intimately linked to stock market performance assessments. An increase in stock prices offers investors larger rewards and indicates a good acceleration of economic activity. Conversely, a sudden or persistent drop in share prices suggests that the economy is deteriorating and that investment risks may be higher than is reasonable. To make wise selections and achieve sizable gains, investors must be able to forecast the direction of stock prices with high accuracy. Additionally, stock price forecasting contributes in the advancement of stock pricing theory and the stock market's financing function (Zhu et al., 2024). One of the classic trading arenas is the stock market, where anybody may trade stocks with ease and make or lose money. People who are solely aware of profit or loss have misunderstandings about the stock market and believe it to be a gambling environment. Therefore, data science, big data processing, more human awareness, and transparent approaches to the business information presented are countering this image that results from a lack of suitable knowledge and analytical abilities. Furthermore, in order to address this difficulty, attempts are being made at a quick pace to develop a precise, reliable, and efficient model to forecast changes in stock prices (Karim et al, 2021).

An essential component of investing decision-making has been fundamental analysis, one of the most conventional techniques for predicting stock prices that is based on the evaluation of a company's inherent worth. This method forecasts a company's future profits and possible stock price movement by analyzing financial statistics, earnings reports, and macroeconomic factors. In a similar vein, technical analysis forecasts future price movements by utilizing charts, technical indicators, and past price trends. Although technical and fundamental analysis can offer insightful information, they may miss short-term market dynamics and outside events and have limited forecasting power. Currently, there has been a lot of interest in the use of machine learning in financial forecasting, especially stock price prediction, in recent years. Machine learning algorithms can process large amounts of data and identify complex patterns that traditional methods often fail to detect (Kabir et al., 2023: 947). For researchers, forecasting the future has always been an exciting and alluring undertaking. Given this, forecasting stock market price changes is thought to be a more intriguing area of study since it provides crucial hints regarding the loss/gain balance. Scholars from several disciplines, such as computer and business sciences, have conducted study on stock market forecasting. In order to anticipate the market, researchers have been experimenting with a variety of methods, systems, and combinations. Based on the variables that might affect the stock's market performance, the forecasting model's characteristics were created (Usmani et al., 2016: 322). However, price movements are only a tiny part of all market data, and because financial markets are continually connected to social events, it may be extremely difficult or impossible to anticipate the stock price accurately based solely on price movements (Miah et al, 2015: 5). Despite forecasting's many drawbacks and challenges, several research has demonstrated that machine learning approaches are more effective than conventional ones (Li et al, 2017; Bhattacharjee and Bhattacharja, 2019; Qihang, 2020).

Even though there are significant challenges, such the complexity of stock market forecasting, the disparities between the results of conventional and modern approaches, and the fact that several factors can influence share prices at the same time, the area is becoming more and more appealing. In addition to technical information, religious viewpoints influence market players' investing choices. This study's primary driving force is the hypothesis that the price movements of conventional and Islamic-perspective indices may differ from one another, not to mention that these perspectives may potentially have different future projections. In light of this, the goals of the research are to anticipate the future values of a few chosen indices that were created using both Islamic and conventional methods, as well as to suggest a model for price forecasting to market players by identifying the most effective model. For this reason, the future prices of the indices created using criteria from various viewpoints were predicted using the conventional ARIMA model as well as the algorithms from the LSTM, XGBoost, and Decision tree models in Appendix 1, which are machine learning models. Following the studies, the machine learning models were optimized to identify the optimal hyperparameters, and hybrid XGBoost-Decision Tree, LSTM-XGBoost, and LSTM-Decision Tree models were created. Twelve indices—six conventional and six Islamic—and eighty-four distinct models—three conventional, three machine learning, and three hybrid models—were developed within this framework using seven methods. In light of this motivation and goal, the study compares the outcomes of various models in indices built using conventional and Islamic viewpoints and gives market players the chance to assess the aforementioned viewpoints and models.

First, the academic literature in the topic is mentioned in this research. Methodological justifications of the data collection and the techniques for the study are then provided. After the outcomes of the hybrid model and the methodologies used have been analyzed and interpreted, the research is ended with final assessments.

LITERATURE REVIEW

This section highlights some of the scholarly research on the techniques created for stock market future forecasting and the results acquired.

In the field of Artificial Neural Networks (ANN), Hossain et al. (2018) aimed to address regression-related challenges by leveraging deep learning techniques. They developed a hybrid model incorporating Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) to forecast future values of the S&P 500 Index from 1950 to 2016, utilizing evaluation metrics such as mean squared error and mean absolute percentage error. With an RMSE score of 0.031, the results demonstrated the hybrid model's effectiveness in generating accurate predictions. Additionally, Manasa and Reddy (2024) employed nine machine learning models including Decision Tree, Random Forest, Adaptive Boosting (Adaboost), eXtreme Gradient Boosting (XGBoost), Support Vector Classifier (SVC), Naive Bayes, K-Nearest Neighbors (KNN), Logistic Regression, and Artificial Neural Networks—to minimize uncertainty in trend forecasting through machine learning and deep learning techniques. Their findings indicate that for sequential data, RNN and LSTM outperform other predictive models. Similarly, Oukhouya et al. (2024) conducted a study on modeling and forecasting daily stock index prices including MASI, CAC 40, DAX, FTSE 250, NASDAQ, and HKEX, representing the markets of Morocco, France, Germany, the UK, the USA, and Hong Kong. They evaluated the performance of machine learning models such as Long Short-Term Memory (LSTM), eXtreme Gradient Boosting (XGBoost), and a hybrid LSTM-XGBoost approach. The results showed that the hybrid LSTM-XGBoost model, when optimized using Grid Search (GS), outperformed other models and achieved higher accuracy in daily price predictions. Tong et al. (2023) employed the closing prices of six firms to examine the predicting performance of ARIMA, LSTM, XGBoost, and hybrid models. The results of empirical research indicate that, for all six organizations, the hybrid model performs the best. (2024) sought to develop a sophisticated forecasting model for stock market price movements by fusing the ARIMA algorithm with XGBoost machine learning. The results highlight the effectiveness of fusing traditional time series analysis with cutting-edge machine learning, establishing the ARIMA-XGBoost hybrid model as a potent instrument for precise and reliable stock market trend forecasting, even though the hybrid model outperforms standalone ARIMA and XGBoost models in terms of accuracy. Additionally, Kumar et al. (2022) used SARIMA and XGBoost-based machine learning to predict the value of publicly traded stocks. They discovered that the suggested SARIMA-XGBoost hybrid model outperforms conventional forecasting techniques, demonstrating an accuracy of 89.48% and a mean absolute error (MAE) of 15.612. Moreover, the study conducted by Oukhouya and Himdi (2023) sought to model and forecast the daily values of the Moroccan Stock Index 20 (MSI 20). The outcomes of using different machine learning techniques are contrasted in this framework. Support Vector Regression (SVR), eXtreme Gradient Boosting (XGBoost), Multilayer Perceptron (MLP), and Long Short Term Memory (LSTM) models were compared using the Grid Search (GS) optimization algorithm. It was discovered that SVR and MLP models performed better than the other models and had high accuracy in predicting daily prices.

In order to anticipate stock prices, Jing et al. (2021) suggest a hybrid research model that integrates sentiment analysis and deep learning techniques using CNN and LSTM Neural Networks. According to analyses using data from the Shanghai Stock Exchange, the suggested model does a superior job of categorizing investor mood. Plus, after saving the analysis and prediction findings, Liwei et al. (2021) employed the LSTM model to generate a new test set and forecast the retained characteristics. In addition, the Bo-XGBoost model, which was based on XGBoost, was used to train the first training set. According to this study, the suggested LSTM-BO-XGBoost model fared better in stock price predictions than the LSTM. WT-ARIMA LSTM is a new hybrid model for stock price index futures forecasting that was proposed by Zang et al. (2024). This hybrid model uses the ARIMA-LSTM model to forecast the closing price of futures and the wavelet transform to break down stock price index futures and extract data features at various time scales. They find that when the forecasting performance in various markets and the method's operational efficiency are coupled, the DWT ARIMA-LSTM model can have improved forecasting performance.

METHODOLOGY

In this section of the research, the data set considered, the methods applied and the hybrid models constructed are explained in detail. Finding the best model to forecast future price movements of the world's top Islamic and conventional indices—the MSCI, MSCI Shariah, Nifty 50, Nifty 50 Shariah, FTSE 100, FTSE Shariah, S&P 500, S&P Shariah, Dow Jones, Dow Jones Shariah, BIST 100, and BIST Participation 100 Indices—as well as suggesting a suitable hybrid model are the goals of the research. Daily closing data for the indices used in the study is sourced from the Yahoo Finance and Data Stream databases for this purpose. There may be variations in the date limitation since each index is examined separately in the research. In consideration of this, Table 1 summarizes the indices, codes, and time periods that were part of the analysis. Although a large number of indices designed according to the traditional perspective or constructed from the Islamic perspective are calculated all over the world, some prominent indices are taken into consideration in this study. The reason for this is that the sample size may be sufficient to test the models that may be prominent in the price forecasting of Islamic and conventional indices. It can be said that the hybrid models to be presented as a result of the research will be a reference for other indices by market participants.

Table 1. Indices Included in the Analysis

Indices	Index code	Period of analysis
MSCI	MSCI	25.06.2009-25.06.2024
DOW JONES	^DJI	25.06.2004-25.06.2024
FTSE 100	^FTSE	25.06.2004-25.06.2024
NIFTY 50	^NSEI	25.06.2009-25.06.2024
S&P 500	^SPX	25.06.2004-25.06.2024
BİST 100	XU100.IS	25.06.2004-25.06.2024
MSCI WORLD ISLAMIC MARKET	ISWD.L	25.06.2009-25.06.2024
DOW JONES WORLD ISLAMIC MARKET	^DJIMI	25.06.2004-25.06.2024
FTSE SHARIAH	HLAL	17.07.2019-25.06.2024
NIFTY 50 SHARIAH	SHARIABEES	12.06.2014-12.06.2024
S&P 500 SHARIAH	^SP500SH	07.04.2008-25.06.2024
BİST Participation 100	XK100.IS	12.11.2021-25.06.2024

To achieve the goal of the research, each index is analyzed independently. The ARIMA model is first created using the Akaike information criterion after each index has undergone the unit root test. All indexes are then adjusted for seasonality using the SARIMA seasonality test. After XGBoost, LSTM, and Decision Tree models were applied to each model, the best parameters from each model were determined to create hybrid models. In the next stage, three different hybrid models were created: XGBoost-LSTM, XGBoost-Decision Tree, and LSTM-Decision Tree. Each hybrid model was applied separately to 12 indices. A total of 84 model outputs were therefore obtained, with a distinct model being produced by each technique. Each model's output was the Root Mean Square Error of Squared Error (RMSE) values, which serve as the study's estimate criteria. In the field of statistics, RMSE is employed to assess a model's performance. To put it another way, RMSE is an error statistic that assesses how well a regression model's predictions match the actual data. The RMSE is computed as follows and indicates the degree to which the forecasts differ from the actual values (Göğen and Güney, 2024:2325):

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

Below is a detailed presentation of the hybrid models ARIMA, XGBoost, LSTM, and Decision Tree as well as their methodology for the research.

ARIMA (Box-Jenkins Method) Model

ARIMA models, developed by Box and Jenkins in 1970, are also referred to as the Box-Jenkins methodology, which consists of a series of activities for forecasting and identification, centred on time series data. The model is one of the most prominent methods in financial forecasting. ARIMA models have shown effective efficiency in generating short-term forecasts. It performs better than complex structural models, especially in short-term forecasting. In the ARIMA model, the future value of a variable is expressed as a linear combination of past values and past errors expressed as follows (Ariyo et al, 2014:106):

$$X'_t = \emptyset_1 X'_{t-1} + \emptyset_2 X'_{t-2} + \cdots + \emptyset_p X'_{p-2} + Y_t + \emptyset_1 X_{t-1} + \emptyset_2 X_{t-2} + \cdots + \emptyset_q X_{t-q} \quad (2)$$

The autoregressive moving average (ARMA) is recognised as a highly accurate linear time series forecasting model suitable for stationary time series for forecasting. The actual load sequence is a typical non-stationary time series, so before modelling with ARMA, the actual load sequence needs to be transformed into a smooth time series. The differential transformation is categorized into sequential and periodic differential transformations. The model is computationally refined using the Akaike Information Criterion, while parameter estimation methods include moment estimation, least squares estimation, and maximum likelihood estimation. Once the model ordering and parameter estimation are finalized, the ARMA model predicts the stationary differenced sequence. The obtained forecast is then processed through inverse differential transformation to derive the final predicted value (Xiao et al., 2020: 5381).

LSTM (Long Short Term Memory) Model

The LSTM (Long Short Term Memory) model proposed by Hochreiter and Schmidhuber (1997) is designed to overcome error backflow problems. With this model one can learn to bridge time intervals exceeding 1000 steps without losing short time delay capabilities even in the case of incompressible input sequences. This can be achieved with an efficient, gradient-based algorithm for an architecture that enforces a constant (hence neither bursty nor fading) error stream across the internal states of specialized units (Hochreiter and Schmidhuber, 1997:1736) Furthermore, the LSTM is a modified version of the RNN (Recurrent Neural Network). Since RNN can analyze time series models, it is considered as one of the most suitable methods for stock price prediction and is expressed by the following formula (Bathla, 2020):

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

LSTM models, like other deep learning models, are trained with large amounts of data. In the training process, the backpropagation algorithm is used and the loss functions are minimized in order to set the internal gates of the LSTM appropriately. In addition, LSTM layers serve as the fundamental components of the model, enabling the processing of input sequences and capturing dependencies among input features (Han and Fu, 2023: 52). Additionally, as a specialized type of Recurrent Neural Networks (RNNs), LSTMs effectively mitigate the issues of exploding and vanishing gradients through their integrated memory cell and gate mechanism. The LSTM architecture comprises blocks with input (i_t), forget (f_t), and output (o_t) gates, forming a recursive structure where the output of one block is sequentially fed into the next. The use of LSTM models in stock market forecasts allows for near-accurate forecasts by effectively capturing long-term dependencies (Oukhouya et al., 2024:203).

XGBoost Model

The Extreme Gradient Boosting (XGBoost) model is essentially a gradient boosting decision tree designed to enhance prediction speed and efficiency. In other words, it is an optimized version of the boosting algorithm that constructs decision trees by iteratively adding trees and splitting features (Dai et al., 2022: 5). Originally developed by Chen and Guestrin (2016), XGBoost is a powerful machine learning algorithm recognized for its efficiency and computational speed. By leveraging gradient-based decision trees for effective feature selection, it delivers strong performance in stock market forecasting, benefiting from its parallelization and scalability capabilities. The model's equation is as follows:

$$\sum_{i=1}^{n} = L(y_i, p_i) + \frac{1}{2}\alpha 0_v^2 \quad (4)$$

The term "XGBoost" represents an engineering objective aimed at maximizing computing resources for boosted tree algorithms. It is built on the Gradient Boosting framework, which serves as the foundation for the machine learning techniques utilized in this system. With its parallel tree boosting capability, XGBoost enables rapid and accurate solutions to complex data science challenges (Oukhouya et al., 2024: 202). The algorithm's parallel processing allows it to handle problems involving billions of instances efficiently across distributed environments using the same code. Additionally, XGBoost helps mitigate data overfitting by storing the model in memory at a single instance, allowing for fine-tuning to enhance predictive accuracy. This tuning process leverages scalability and cache optimization to fully utilize available hardware resources, ultimately improving model performance (Kumar et al., 2022).

Decision Tree Model

Classification in machine learning involves a variety of algorithms, and in this study we focus on the decision tree algorithm in general. Decision trees are highly effective techniques commonly applied in fields such as machine learning, image processing, and pattern recognition. They function as sequential models that systematically integrate a series of fundamental tests, where each test involves comparing a numerical feature to a predefined threshold value (Jijo and Abdulazeez, 2021: 21). The Decision Tree (DT) is a widely used data mining technique for various prediction tasks, offering reliable classification and forecasting capabilities. Its tree-like structure consists of multiple nodes and branches, which expand based on different conditions. Each node represents an output or target class, while each branch signifies a decision process for classification. The final node provides the predicted outcome, and once the decision tree model is constructed, the error rate during pruning can be assessed. Pruning is a crucial process that enhances the model's classification and prediction accuracy, leading to more efficient decision-making. Unlike Artificial Neural Networks (ANNs), DT also produces a structured set of decisions and rules, facilitating further analysis (Tsai and Wang, 2009).

Hybrid Models

Machine learning hybrid models were developed in this section of the research to forecast the future price behavior of the MSCI, MSCI Shariah, Nifty 50, Nifty 50 Shariah, FTSE 100, FTSE Shariah, S&P 500, S&P Shariah, Dow Jones, Dow Jones Shariah, BIST 100, and BIST Participation 100 Indices. Figure 1 displays the flow diagram for the XGBoost-Decision Tree, LSTM-Decision Tree, and LSTM-XGBoost hybrid models.

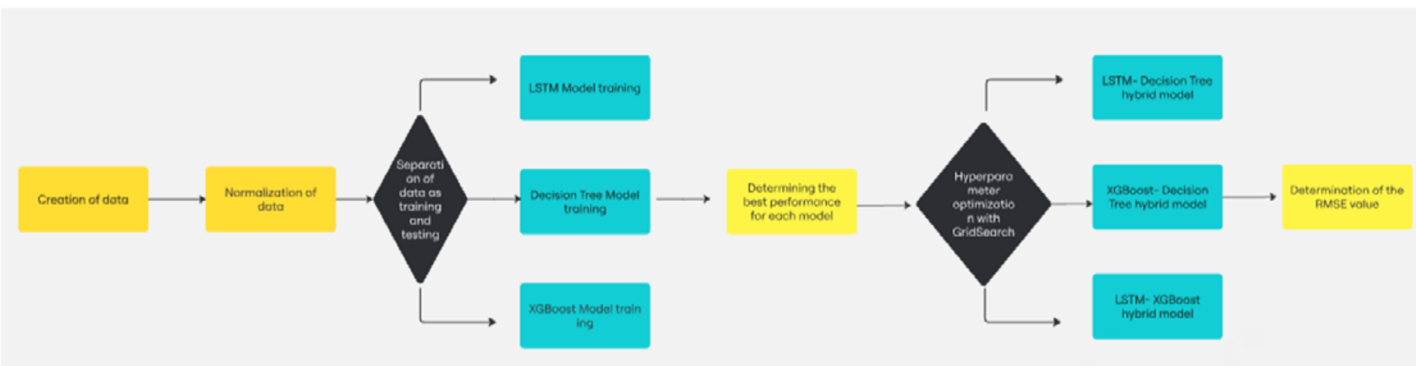


Figure 1. Hybrid Model Flow Diagram, Source: Created by the authors.

As long as same methodological steps are followed for each model used, such classifying the data according to time series and normalizing it for the Decision Tree algorithm to prevent problems with algorithm scaling and performance. After that, the data set was divided into 70% training groups and 30% test groups. In order to determine the optimal parameters for the model, the GridSearch method—a 5-fold time series split cross-validation technique on the training set—was used to optimize the hyperparameters and identify the best-performing parameters and hyperparameters after the model was created and the data set was trained (Oukhouya et al., 2024:204). This procedure was applied to all machine learning models. Subsequently, the best models from each algorithm were selected based on the hyperparameters found, and hybrid models were created by combining the best models from each algorithm with machine knowledge models. To find the RMSE value of the hybrid models (XGBoost-Decision Tree hybrid model, LSTM-Decision Tree hybrid model, and LSTM-XGBoost hybrid model), the voting model, meta-modelling (Stacking), weighted average, and linear combination approaches were investigated. It was decided to choose the weighted average model with the lowest value. The hybrid model's final RMSE value was computed using the value obtained from the chosen model.

FINDINGS and ANALYSIS

When trading stocks and commodities, people mostly depended on intuition prior to the last several decades. The rise in trade and investment levels has led businesses to seek out methods and tools to increase earnings while reducing risks. Market moves are predicted and profited from using statistics, technical/fundamental analysis, and linear regression. No one of these approaches has consistently provided the necessary degree of prediction accuracy, and many analysts still doubt their usefulness. In spite of this, these methods are provided since they are often used in practical situations and provide a standard by which AI may evaluate itself. More often than not, these techniques are used to pre-process raw data inputs (Miah et al., 2015:5).

For the future price forecasts of six Islamic and six conventional indices, 84 different algorithms were developed using the Pyhton Jupyter Notebook program. These algorithms included ARIMA, XGboost, LSTM and XGBoost-Decision tree hybrid models, LSTM-Decision Tree hybrid model, LSTM-Decision Tree hybrid model, and LSTM-XGBoost hybrid model. Data sets were split into 70% training and 30% test groups for 84 analysis across all indices. The assessments for the MSCI, MSCI Shariah, Nifty 50, Nifty 50 Shariah, FTSE 100, FTSE Shariah, S&P 500, S&P Shariah, Dow Jones, Dow Jones Shariah, BIST 100, and BIST Participation 100 Indices were conducted using the ARIMA, LSTM, and XGBoost models. These models' algorithms are shown in Appendix 1. The research's conventional technique was solely included to demonstrate that machine learning and hybrid models yield better outcomes than traditional methods.

Table 2. Recommended values for parameter optimisation

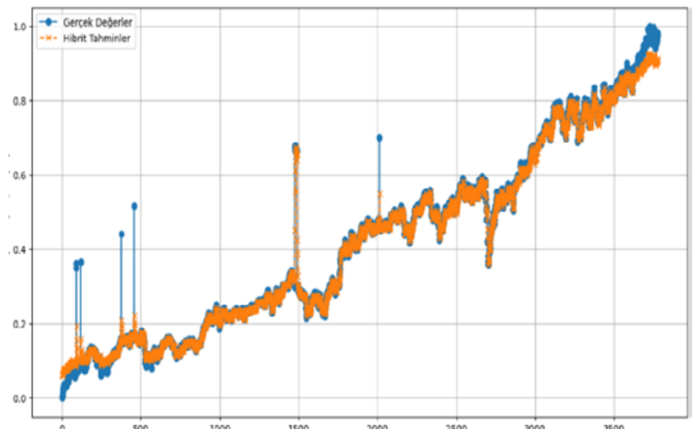
Model	Parameter	Values
XGBoost	**Number of Predictors Learning Rate Maximum Depth Column sampling rate**	**100, 200, 300, 700, 1000 0.001, 0.01, 0.05, 0.1, 0.2 3, 4, 5, 6, 7 0.3,0.7**
Decision Tree	**Maximum Depth Minimum number of samples for node splitting**	**3, 5, 7, 9 2, 5, 10**
LSTM	**Units (number of cells) Activation Optimiser Learning Rate**	**50 Relu Adam, rmsprop, sgd 0.001, 0.01**

The suggested value ranges for hyperparameter optimization for the XGBoost, Decision Tree, and LSTM models utilized in this investigation are shown in Table 2. These parameters were chosen with the goal of enhancing model performance in mind, and each parameter's value range is organized according to prior research in the field as well as the outcomes of empirical tests. For the XGBoost model, the number of predictors is taken into account in a broad range (between 100 and 1000). This made it possible to test the model's complexity in a methodical manner. Sensitive values for the learning rate model ranged from 0.001 to 0.2. We were able to assess the model's performance at both low and high learning rates because to this variance. Values between 3 and 7 were chosen for Maximum Depth in an effort to counteract the model's propensity to overlearn. To maximize the model's responses to subsets of variables, the Column Sampling Rate was selected between a narrow range of 0.3 and 0.7. It was attempted to balance the decision tree model's overfitting tendency with the maximum depth parameter (3, 5, 7, 9). In parallel, the model's ability to generalize was evaluated using the fewest possible samples for nodes (2, 5, 10). The building elements that are often chosen in deep learning architectures were taken into consideration when creating the LSTM configurations. ReLU was favored as the activation function, and the number of cells (units) was set at a constant 50. Its goal is to model non-linear connections in this way. Adam, RMSprop, and SGD were all assessed together as optimization algorithms, enabling a comparison of the dynamics of parameter updates. To balance the model's speed and stability, the learning rate was also evaluated at low values as 0.001 and 0.01.

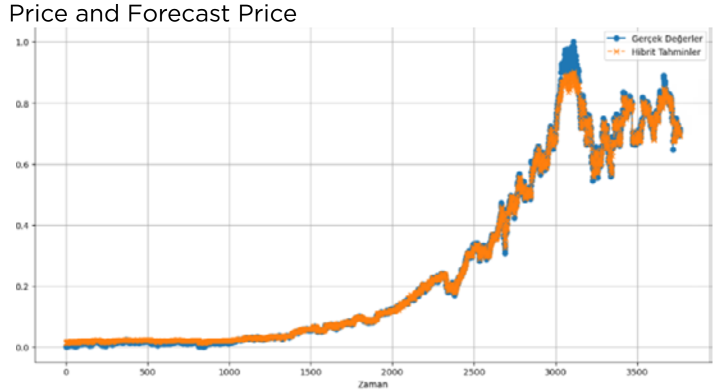
Table 3. Model Outputs and RMSE Value Results for Selected Indices

	Traditional Model	Machine Learning Models			Hybrid Models		
	ARIMA	LSTM	XGBoost	Decision tree	XGBoost-Decision tree	LSTM-Decision tree	LSTM-XGBoost
MSCI Islamic Index	(0.1.2) 1117,43	7,82	37,48	84,17	36,41	0,10	0,022
Nifty 50 Shariah Index	(2.1.1) 121,54	2,01	4,91	6,76	4,87	0,063	0,021
FTSE Shariah Index	(2.1.2) 5,43	0,58	0,70	0,63	0,47	0,044	0,028
S&P Shariah Index	(5.2.0) 2161,66	25,49	35,56	42,14	32,11	0,136	0,014
Dow Jones Islamic Index	(5.0.2) 1960,34	25,11	39,16	51,26	35,31	0,132	0,012
BİST Katılım 100	(0.1.0) 1490,36	74,13	1150,26	935,16	161,89	0,039	0,058
Nifty 50	(0.1.0) 8407,79	48,41	192,19	158,85	0,46	0,136	0,018
FTSE 100	(2.1.4) 1221,99	27,66	77,42	84,69	65,81	0,023	0,022
S&P 500	(2.1.2) 2199,16	7,93	52,94	21,75	28,87	0,12	0,013
MSCI	(2.1.2) 398,60	1.43	11,61	1,86	6,54	0,18	0,016
Dow Jones	(5.0.3) 9476,53	69,33	394,23	180,43	246,01	0,10	0,013
BİST 100	(0.1.0) 63892,92	114,90	3812,21	1412,37	1086,48	0,066	0,024

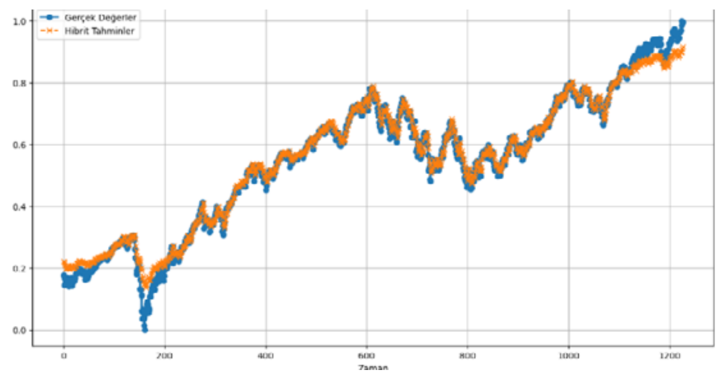
The RMSE values derived from the studies of 84 algorithms for one conventional approach, three machine learning methods, and three distinct hybrid model proposals with the daily closing prices of 12 indices (6 traditional and 6 Islamic) are displayed in Table 3. A popular metric for evaluating forecast accuracy is RMSE, and lower RMSE values indicate more accuracy. When compared to other models, the ARIMA model often yields results with high RMSE values. This demonstrates that for intricate and nonlinear financial time series, ARIMA's linear assumptions are insufficient. The ARIMA model performs noticeably poorly, particularly in the BIST Participation 100 (RMSE: 1490.36) and BIST 100 (RMSE: 63892.92) indices. For several indices, LSTM models are shown to provide lower RMSE values than other machine learning models. This is because time-dependent data may be used to teach the LSTM long-term dependencies. For instance, the Decision Tree model's LSTM RMSE is 0.63, but the FTSE Shariah Index's is just 0.58. Notably, the LSTM-XGBoost model obtains the lowest RMSE value for practically all indices when the hybrid models' performance is examined. Particularly in the MSCI Islamic Index (0.022), Nifty 50 Shariah (0.021), and S&P Shariah (0.014) indices, the superiority of this strategy is evident. With the lowest error value (0.018) for the BIST Participation 100 index, the LSTM-Decision Tree model also demonstrated excellent performance overall. These results demonstrate that hybrid models may more successfully represent intricate structures in financial time series and attain accuracy levels that surpass those of traditional techniques. More efficient price prediction models are produced by combining the sequential data learning capabilities of LSTM with the decision boundary optimization capabilities of XGBoost and Decision Tree. As a result, it is advised that hybrid models be given preference when it comes to risk reduction and market participants' decision support.



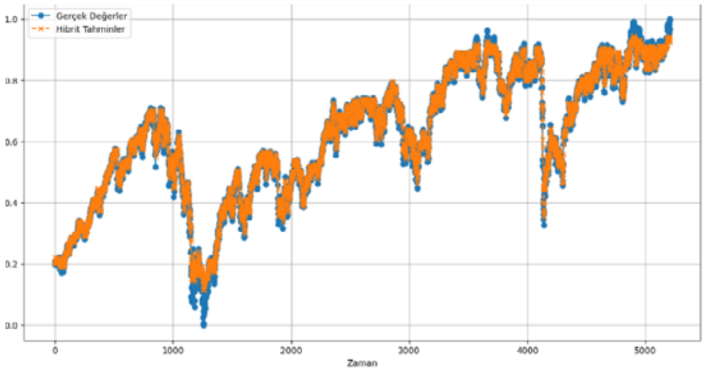
Graph 1. MSCI Islamic Index Closing Price and Forecast Price



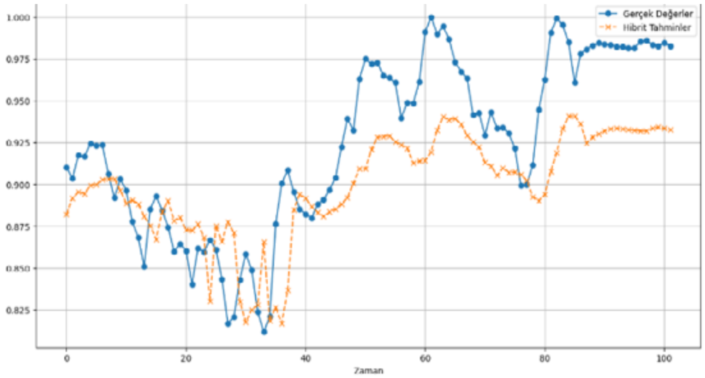
Graph 2. MSCI Index Closing Price and Forecast Price



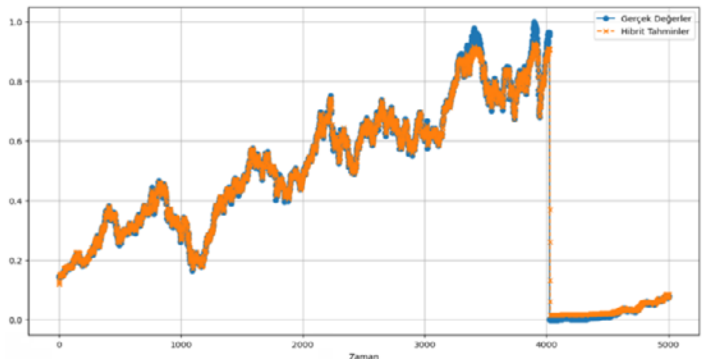
Graph 3. FTSE100 Shariah Index Closing Price and Forecast Price



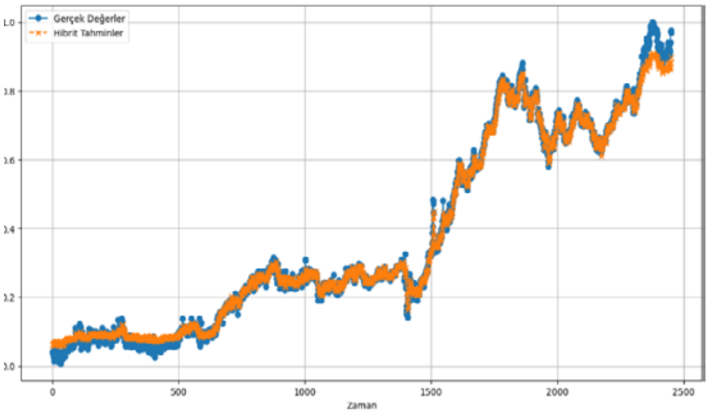
Graph 4. FTSE 100 Index Closing Price and Forecast Price



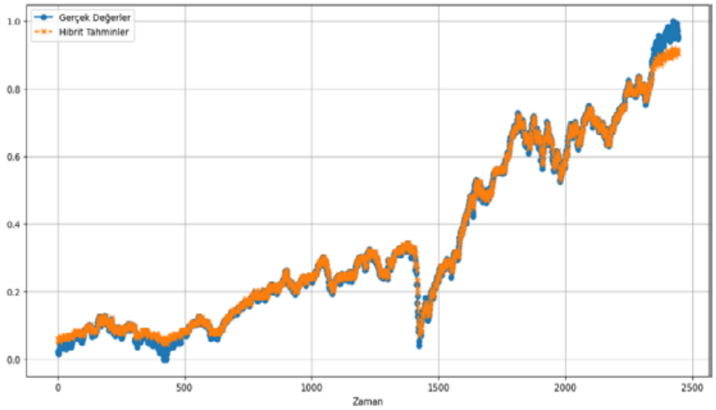
Graph 5. BIST Participation 100 Index Closing Price and Forecast Price



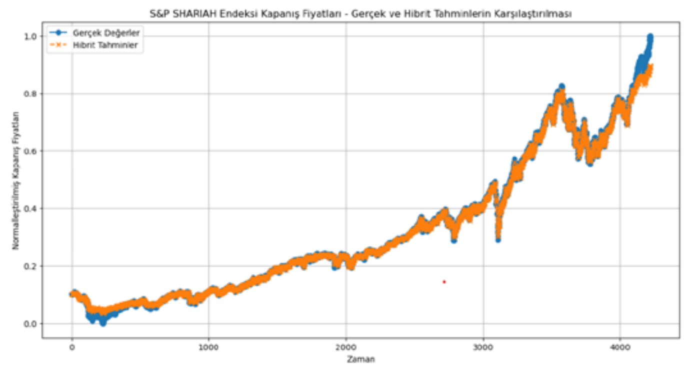
Graph 6. BIST 100 Index Closing Price and Forecast Price



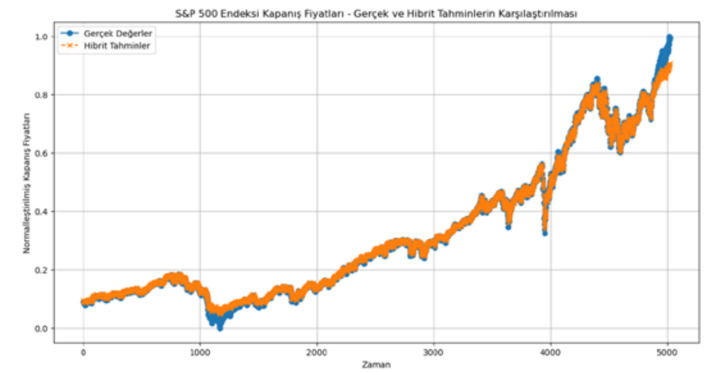
Graph 7. Nifty 50 Shariah Index Closing Price and Forecast Price



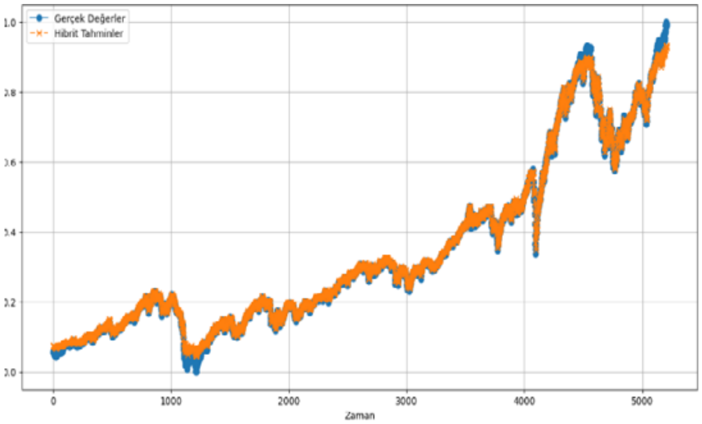
Graph 8. Nifty 50 Index Closing Price and Forecast Price



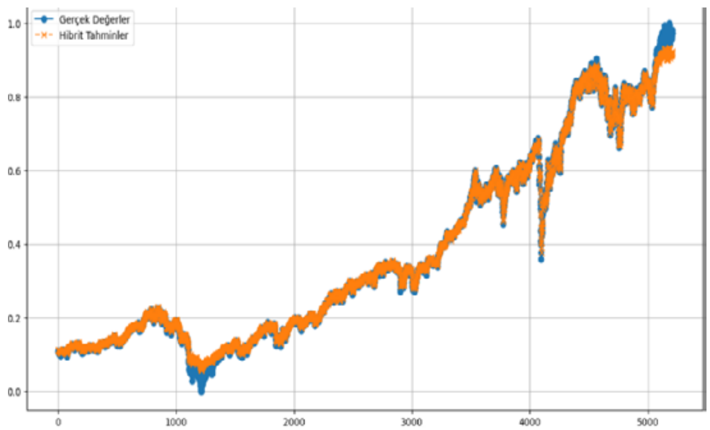
Graph 9. S&P Shariah 500 Index Closing Price and Forecast Price



Graph 10. S&P 500 Index Closing Price and Forecast Price



Graph 11. Dow Jones Islamic Index Closing Price and Forecast Price



Graph 12. Dow Jones Index Closing Price and Forecast Price

The closing and forecast price processes of the hybrid models that yield the optimal RMSE value for each index are shown in Graphs 1–12. The graphs' blue line displays the closing values as of right now, while the red line represents the expected prices for both indices. The results of the LSTM-XGBoost hybrid model, which is the most successful model for the other 11 indices, and the LSMT-Decision Tree hybrid model, which is the most successful model for the BIST Participation 100 Index, show that the closing price and forecast price curves move very closely. Thus, it can be concluded that the reliability of the findings and the validity of the related models are supported.

CONCLUSION

Since it is in charge of managing and allocating funds and resources, the financial sector is among the most significant in the world. With the advent of several technical advancements throughout the years, the industry has experienced notable expansion and advancement. The application of machine learning algorithms is among the most significant recent advancements. All market participants closely monitor the shortcomings of traditional methods' fundamental presumptions, the low degree of their dynamic structures, and -above all- the route paved by artificial intelligence-supported techniques like machine learning in order to achieve sharper results. New models and applications are also continuously being developed. However, even if predictions are based on objective data sets, it is indisputable that people's attitudes have an impact on this facts. In light of this, this study uses ARIMA to analyze the future price forecasts of a few indices that are well-known worldwide and computed from an Islamic perspective and traditional plane: MSCI, MSCI Shariah, Nifty 50, Nifty 50 Shariah, FTSE 100, FTSE Shariah, S&P 500, S&P Shariah, Dow Jones, Dow Jones Shariah, BIST 100, and BIST Participation 100 Indices. Along with XGBoost, LSTM, and Decision Tree models, the goal is to identify which hybrid models- XGBoost-Decision Tree, LSTM-Decision Tree, and LSTM-XGBoost-produced via hyperparameter optimization provide the best outcomes. The findings of many models have been ascertained for this goal in the indices chosen with varying research perspectives. The study offers both a viewpoint comparison and a model-based comparison in this regard. In the perspective of various models, a comparison among comparable viewpoints is also given.

Using seven algorithms and eighty-four models, the research produced twelve indices, six traditional, six

Islamic, one traditional, three machine learning, and three hybrid models. The results gathered showed that the LSTM model performed the best across all indices. The LSTM-XGBoost model was shown to perform the best throughout the range of hybrid models constructed for both standard and Islamic indices, with the exception of the BIST Participation 100 Index data, where the LSTM-Decision Tree model was the top estimator. Although this research had predicted that the models' effectiveness in forecasting future prices may vary, it was discovered that there was no appreciable difference between the methods that could be preferred in prediction between Islamic and traditional based indices (with the exception of the BIST Participation 100 Index). These results imply that hybrid techniques, as opposed to just classical or machine learning-based methodologies, may offer superior prediction accuracy. It is determined that more dependable assistance for financial market decision-making processes can be obtained by fusing the powerful classification powers of XGBoost and Decision Tree with the temporal learning capability of LSTM models.

The research results are similar to those of studies by Oukhouya et al. (2024), Liwei et al. (2021), and Tong et al. (2023). In contrast to past studies in the relevant literature, this study is unique and contributes to the field by assessing 84 different models from an Islamic and conventional perspective and providing suggestions for hybrid models to market players. It is anticipated that testing the proposed hybrid models on other indices, developing new models, and making them usable would greatly progress the field in future studies.

REFERENCES

Ariyo, A., Adewumi, A., & Ayo, C. (2014). Stock price prediction using the ARIMA model. In 2014 UKSim-AMSS 16th international conference on computer modelling and simulation (s. 106-112). IEEE.

Bhattacharjee, I., & Bhattacharja, P. (2019). Stock Price Prediction: A Comparative Study between Traditional Statistical Approach and Machine Learning Approach. 4th International Conference on Electrical Information and Communication Technology (EICT). IEEE.

Dai, Y., Zhou, Q., Leng, M., Yang, X., & Wang, Y. (2022). Improving the Bi-LSTM model with XGBoost and attention mechanism: A combined approach for short-term power load prediction. Applied Soft Computing, 130. doi:https://doi.org/10.1016/j.asoc.2022.109632

Göğen, E., & Güney, S. (2024). Machine learning-based weather prediction with radiosonde observations. Journal of the Faculty of Engineering and Architecture of Gazi University, 39(4), 2317-2328. doi:10.17341/gazimmfd.1163079

Han, C., & Fu, X. (2023). Challenge and Opportunity: Deep Learning-Based Stock Price Prediction by Using Bi-Directional LSTM Model. Frontiers in Business, Economics and Management, 8(2), 51-54.

Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. Neural computation. 9(8), 1735–1780.

Hossain, M., Karim, R., Thulasiram, R., Bruce, N., & Wang, Y. (2018). Hybrid deep learning model for stock price prediction. In 2018 ieee symposium series on computational intelligence (ssci) (s. 1837-1844). IEEE.

Jijo, B., & Abdulazeez, A. (2021). Classification Based on Decision Tree Algorithm for Machine Learning. ournal of Applied Science and Technology Trends, 2(1), 20-28.

Jing, N., Wu, Z., & Wang, H. (2021). A hybrid model integrating deep learning with investor sentiment analysis for stock price prediction. Expert Systems with Applications, 178. doi:https://doi.org/10.1016/j.eswa.2021.115019

Kabir, M., Sobur, A., & Amin, M. (2023). Stock Price Prediction Using the Machine Learning. nternational Journal of Computer Research and Technology (IJCRT), 11(7), 946-950.

Karim, R., Alam, M., & Hossain, M. (2021). Stock market analysis using linear regression and decision tree regression. In 2021 1st International. In 2021 1st International Conference on Emerging Smart Technologies and Applications (eSmarTA) (s. 1-6). IEEE.

Kumar, D., Thiruvarangan, B., Reddy C, S., Vishnu, A., Devi, A., & Kavitha, D. (2022). Analysis and prediction of stock price using hybridization of sarima and xgboost. In 2022 International Conference on Communication, Computing and Internet of Things (IC3IoT) (s. 1-4). IEEE.

Li, L., Wu, Y., Ou, Y., Li, Q., Zhou, Y., & Chen, D. (2017). Research on machine learning algorithms and feature extraction for time series. In 2017 IEEE 28th annual international symposium on personal, indoor, and mobile radio communications (PIMRC) (s. 1-5). IEEE.

Liwei, T., Li, F., Yu, S., & Yuankai, G. (2021). Forecast of LSTM-XGBoost in Stock Price Based on Bayesian Optimization. Intelligent Automation & Soft Computing, 29(3), 855-868. doi:http://dx.doi.org/10.32604/iasc.2021.016805

Manasa, M., & Reddy, A. (2024). Stock Market Prediction Using Machine Learning and Deep Learning Algorithms. UGC Care Group I Listed Journal, 14(1), 49-60.

Mehak, U., Adil, S., Raza, K., & Ali, S. (2016). Stock Market Prediction Using Machine Learning Techniques. 2016 3rd International Conference On Computer and Information Sciences (ICCOINS) (s. 322-327). IEEE.

Miah, M., Hossain, M., Hossain, M., & Islam, M. (2015). Price prediction of stock market using hybrid model of artificial intelligence. International Journal of Computer Applications, 111(3).

Oukhouya, H., & Himdi, K. (2023). Comparing machine learning methods—svr, xgboost, lstm, and mlp—for forecasting the moroccan stock market. Computer Sciences & Mathematics Forum, 7(1), 39.

Oukhouya, H., Kadiri, H., Himdi, K., & Guerbaz, R. (2024). Forecasting International Stock Market Trends: XGBoost, LSTM LSTM-XGBoost, And Backtesting XGBoost Models. (200-209, Dü.) Statistics, Optimization & Information Computing, 12(1).

Qihang, M. (2020). Comparison of ARIMA, ANN and LSTM for stock price prediction. In E3S Web of Conferences. EDP Sciences.

Somkunwar, R., Pimpalkar, A., & Srivastava, V. (2024). A Novel Approach for Accurate Stock Market Forecasting by Integrating ARIMA and XGBoost. In 2024 IEEE International Students' Conference on Electrical, Electronics and Computer Science (SCEECS) (s. 1-6). IEEE.

Tong, Z., Li, H., & Zhang, Y. (2023). A Comparison of ARIMA, LSTM, XGBOOST and Hybrid in Stock Price Prediction. In 2023 5th International Conference on Applied Machine Learning (ICAML) (s. 18-25). IEEE.

Tsai, C., & Wang, S. (2009). Stock price forecasting by hybrid machine learning techniques. In Proceedings of the international multiconference of engineers and computer scientists, Vol.1 No.755, s. 60.

Xiao, C., Xia, W., & Jiang, J. (2020). Stock price forecast based on combined model of ARI-MA-LS-SVM. Neural Computing and Applications, 32(10), 5379-5388. doi:https://doi.org/10.1007/s00521-019-04698-5

Zhang, J., Liu, H., Bai, W., & Li, X. (2024). A hybrid approach of wavelet transform, ARIMA and LSTM model for the share price index futures forecasting. The North American Journal of Economics and Finance, 69. doi:https://doi.org/10.1016/j.najef.2023.102022

Zhu, R., Zhong, G.-Y., & Li, J.-C. (2024). Forecasting price in a new hybrid neural network model with machine. Expert Systems with Applications, 249. doi:https://doi.org/10.1016/j.eswa.2024.123697

Author Contributions
All the authors have equal contributions.

APPENDIX 1:

ARIMA Algorithm

```
from pmdarima import auto_arima
#ignore harmless warnings
import warnings
warnings.filterwarnings("ignore")
stepwise_fit= auto_arima(df['Close'], trace= True, suppress_warning= True)
stepwise_fit.summary()
from statsmodels.tsa.arima_model import ARIMA
print(df.shape)
train=df.iloc[:-'eğitim verisi']
test=df.iloc[-'test verisi':]
print(train.shape, test.shape)
from statsmodels.tsa.arima.model import ARIMA
model= ARIMA(train['Close'], order=(  ))
model=model.fit()
model.summary()
```

LSTM Algorithm

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.optimizers import Adam
from tensorflow.keras import layers

model = Sequential([layers.Input((3, 1)),
                layers.LSTM(64),
                layers.Dense(32, activation='relu'),
                layers.Dense(32, activation='relu'),
                layers.Dense(1)])
model.compile(loss='mse',
        optimizer=Adam(learning_rate=0.001),
        metrics=['mean_absolute_error'])
model.fit(X_train, y_train, validation_data=(X_val, y_val), epochs=100)
```

XGBoost Algorithm

```
from xgboost import XGBRegressor
from sklearn.model_selection import TimeSeriesSplit
from sklearn.model_selection import GridSearchCV
params={'max_depth': [3,4,5,6,7],
      'learning_rate':[ 0.001, 0.01, 0.05, 0.1, 0.2],
      'n_estimators':[ [100, 200, 300, 700,1000],
      'colsample_bytree': [0.3,0.7]}
xgbr=XGBRegressor(seed=20)
model=GridSearchCV(
   estimator=xgbr,
   param_grid=params,
   scoring = 'neg_mean_squared_error',
   n_jobs = -1,
   verbose=1)
model.fit(X, y)
print("Best parameters:", model.best_params_)
```

Decision Tree Algorithm

```
from sklearn.tree import DecisionTreeRegressor
dt_model = DecisionTreeRegressor()
dt_params = {'max_depth': [3, 5, 7, 9], 'min_samples_split': [2, 5, 10]}
dt_grid = GridSearchCV(DecisionTreeRegressor(), dt_params, cv=5, error_score='raise')
dt_grid.fit(X_train, y_train)
dt_model_best = dt_grid.best_estimator_
```