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Stock Price Prediction Using Deep Learning Algorithms Based on Technical Indicators

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ABSTRACT

Accurately forecasting stock prices helps investors decide when and where to invest. However, the dynamic, non-linear, complex, and chaotic nature of the stock market makes price forecasting difficult. Market movements are influenced by many macroeconomic factors such as political events, corporate policies, economic conditions, commodity prices, and bank interest rates. In addition, advances in technology and communication systems allow these events to be processed quickly, causing stock prices to fluctuate rapidly. Banks, financial institutions, and large investors are therefore forced to act quickly, and the complexity of the market makes accurate forecasting even more difficult. Therefore, new and effective methods must be developed for accurate stock price predictions. In this study, technical indicators were utilized to reduce noise in raw data, obtain meaningful results, and enhance prediction accuracy. Artificial Neural Network (ANN) models demonstrate significant efficiency in analyzing financial time series data. The most appropriate parameters for predictions made with ANN were selected using the correlation coefficient method. The objective was to predict stock prices using technical indicators obtained from websites such as Yahoo Finance. Following data preprocessing, various methods were applied, including Single Layer Long Short-Term Memory (LSTM), 3-Layer LSTM, 3-Layer Bidirectional Long Short-Term Memory (BiLSTM), and Hybrid Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM). This model aimed not only to find realistic price estimates but also to reduce the features that influence stock price estimates through technical indicators. The results indicate that the Single Layer LSTM method provides more realistic estimates than other deep learning (DL) techniques.

1. Introduction

A stock exchange is a market where securities of the same type are traded in a certain order. The stock market is frequently characterized as a dynamic, unpredictable, and non-linear system [1].

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Stock exchanges serve as places where not only securities but also commodities are traded. For example, there are cotton exchanges, precious metal exchanges, and commodity exchanges [2].

Stock prices are affected by many factors such as changes in national policies, domestic and foreign economic environments, and international situations [3]. The stock exchange plays an important role in economic activity and meets the capital requirements of enterprises. It serves as a marketplace where buyers and sellers come together to participate in the purchase and sale of financial instruments. Consequently, they formulate their forecasts based on a combination of historical data, current market information, and their own intuitive insights [4].

Traditional statistical methods used in the literature, such as time series analysis and linear regression models, are employed in stock price prediction. With the advancement of technology, methods effective in studies with time series data, such as Artificial Neural Networks (ANN), Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM), have become more preferred. Adebiyi et al., [5] attempted to obtain predictions using ARIMA and ANN for New York stock data, and according to the results obtained, ANN was found to be superior to ARIMA. Anand, [6] used CNN, LSTM, RNN, MLP, and SVM deep learning architectures for predicting stock prices of the world's leading stock exchange, NSE. Considering sudden changes in the system, the CNN model was able to predict more accurately than other techniques. Nikou et al., [7] used LSTM, RF, SVR, and ANN methods for the daily closing price prediction of the iShares MSCI United Kingdom stock exchange. The LSTM method provided better prediction results than other methods in estimating the daily closing price of the iShares MSCI United Kingdom.

In these studies, past data values, technical indicators, and fundamental economic data are generally used. To predict stock prices, two analytical approaches, fundamental analysis and technical analysis, are employed to reduce the noise in raw data. Thus, eliminating unnecessary information in the data will help obtain accurate prediction results. Fundamental analysis and technical analysis are two important approaches used in stock market prediction, each focusing on different aspects of security evaluation. Fundamental analysis involves determining the value of a security by examining the economic, financial, and qualitative factors related to a company or asset [8]. Technical analysis, on the other hand, is a method used to estimate the future price of a security by examining the price movements and transaction volumes of securities on the stock exchange [9]. Technical analysis involves discovering information for trading and investment decisions using past price and transaction volume data [10]. It shows past price movements of stocks with graphs, which provide opportunities to predict future stock prices. Therefore, graphs are used in technical analysis.

This study aims to obtain predictive values using various machine learning algorithms and deep learning models with data that becomes meaningful using technical indicators. The study aims to use the most in-demand deep learning models, namely ANN, CNN, LSTM, and BiLSTM, to make predictions. The second section presents a literature review. The third section provides a comprehensive explanation of the proposed methodology. The fourth section presents the findings of the analysis. The final section includes a discussion and a presentation of the conclusions.

2. Literature Review

Stock price prediction is of critical importance in the context of financial markets. A substantial body of academic research has been conducted over time on the prediction of stock prices. The objective of the literature on stock price prediction is to predict future price movements using various methods and approaches. The efficacy of traditional methods, such as technical and fundamental analysis, has been evaluated in the context of stock price prediction. In recent years, the development of artificial intelligence and machine learning techniques has given rise to novel approaches in stock prediction. These methods have demonstrated considerable success in the domain of stock prediction. However, it should be noted that each method has its own set of advantages and disadvantages. Fundamental analysis is better suited to long-term investment decisions, whereas technical analysis is more effective for short-term trading decisions. The application of machine learning and deep learning techniques has the potential to facilitate more accurate predictions by processing large datasets.

Göçken *et al.,* [11] aimed to determine the effectiveness of using simple moving average and momentum closing price technical indicators to forecast the closing prices of stocks in the Turkish stock market. The study used a hybrid ANN model that combines harmony search (HS) and genetic algorithms (GA) to capture the relationship between technical indicators and stock market performance. GA was used to train the network, while harmony search algorithms were employed to enhance diversity. Among the trained models, the HS showed superior performance on the test set, although it produced higher error rates compared to the GA. The findings showedthat the HS-based ANN model exhibited superior overall performance.

Vijh *et al.,* [1] used both ANN and RF methodologies to predict the daily closing prices of five companies from various sectors. The companies studied were Nike, Goldman Sachs, Johnson & Johnson, Pfizer, and JP Morgan Chase and Co. The models were evaluated using Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) metrics. The findings showed that ANN demonstrated superior performance in predicting stock prices compared to RF.

Lu *et al.,* [3] proposed a method based on CNN and BiLSTM units with an attention mechanism (AM) for forecasting the closing price of the Shanghai Composite Index on the following day over a period exceeding 1,000 trading days. In this approach, a CNN is employed to extract pertinent features from the input data, which are then utilized by a BiLSTM network to predict the stock's subsequent closing price. The AM is used to capture the impact of feature states at different past times on the stock closing price, thereby enhancing prediction accuracy. Compared to the other methods, the CNN-BiLSTM-AM approach offers a dependable means for investors to anticipate stock prices and make informed stock investment decisions.

Selvin *et al.,* [12] employed three distinct deep learning architectures—namely, RNN, LSTM, and CNN—to forecast the prices of TCS and CIPLA companies traded on the NSE. A sliding window approach was employed to evaluate the predictive performance of these models in the short term. The efficacy of the models was assessed through the use of ARIMA error percentages. The results of the stock price prediction demonstrated that the CNN network exhibited a high degree of accuracy in capturing the trends and providing precise forecasts, outperforming the other two models.

Zahedi *et al.,* [13] evaluated the predictability of prices on the Tehran Stock Exchange by applying ANN models and the principal component analysis (PCA) method using 20 accounting variables. The goodness of fit for PCA was determined based on actual values, and the factors influencing Tehran Stock Exchange prices were accurately predicted. The results of the statistical analysis demonstrated that the ANN method exhibited superior performance compared to both the PCA and MLP methods.

Laboissiere *et al.,* [14] put forth a methodology for forecasting the maximum and minimum daily stock prices of three Brazilian energy distribution companies listed on the São Paulo Stock Exchange BM&FBovespa. The proposed methodology is based on the calculation of different features to be analyzed through feature selection, with the objective of identifying the most suitable features for predicting the maximum and minimum daily stock prices for each company. Subsequently, the actual prediction was achieved using ANNs, with performance evaluated through the calculation of mean absolute error (MAE), MAPE, and RMSE.

Nikou *et al.,* [15] employed a range of advanced machine learning algorithms, including Random Forest, Support Vector Machine (SVM), Long Short-Term Memory (LSTM), and Artificial Neural Network (ANN) models, to predict the closing price of the iShares MSCI UK. The models were evaluated using mean absolute error (MAE), mean squared error (MSE), and root mean squared error (RMSE) as error measurements. The findings indicate that the LSTM blocked recurrent network approach exhibits superior performance in forecasting the iShares MSCI UK closing price compared to other methodologies. Additionally, the SVR method demonstrates heightened sensitivity compared to both the neural network and RF.

Çınaroğlu *et al.,* [16] predicted the stock values of Turkish Airlines (TA) traded on BIST. Using daily data from period 2015-2018, the most successful ANN model was determined by comparing the stock values predicted by different ANN models with the actual values in the same period. In the analysis, the stock value was used as output and the BIST 100 and BIST Transportation indices, oil and dollar prices were used as inputs. In the obtained results, it was concluded that the use of ANN for predicting the behavior and trends of stocks is meaningful.

Islam *et al.,* [17] present a comparative study of stock price forecasting using three different methods: ARIMA, ANN, and stochastic process-geometric Brownian motion (GBM). Each method is used to build predictive models using historical stock data collected from Yahoo Finance. The empirical results show that the traditional statistical model and the stochastic model provide a better approximation for next-day stock price prediction than the NN model.

In a similar approach, Nguyen *et al.,* [18] proposed a novel framework, called deep transfer with relevant stock information (DTRSI), which utilizes a deep neural network (DNN) and transfer learning. The initial stage of the process entails the construction of a baseline model comprising LSTM cells. This is intended to facilitate pre-training based on a substantial corpus of data drawn from a diverse array of stocks, with the objective of optimizing the initial training parameters. Secondly, the baseline model aims to implement minor alterations using limited data and different input attributes from the target stock, with the goal of enhancing performance. The input data include information from the five companies in the Korean and United States (US) markets with the highest market capitalization between 2012 and 2018. The experimental results show that the integrating transfer learning and stock relationship data enhances the model's predictive performance, with the proposed approach exhibiting a notable superiority in terms of prediction accuracy.

In a comparative study conducted by Shah *et al.,* [19], two artificial neural networks- namely, the LSTM-RNN and the DNN models, were employed to predict the daily and weekly movements of the Indian BSE Sensex index. To prevent overfitting, measures were taken in both networks. To assess the models' generalizability, daily forecasts for Tech Mahindra (NSE: TEML) stock price were generated. The two networks demonstrated comparable performance in forecasting the daily price movements of Tech Mahindra. The findings indicated that the LSTM-RNN model exhibited superior performance in weekly forecasting compared to the DNN model.

To supplement and expand existing knowledge on stock market forecasting, Kehind *et al.,* [20] conducted a scientometric study. This was done with the aim of reviewing the progress and trends in this field of study, as well as gaining a broader understanding of bibliometric data, tools and methods. The authors employed science mapping and scientometrics techniques for the analysis of bibliometric data and the visualization of scientific knowledge and contributions within a selected field of study. A search was conducted using Scopus, the most comprehensive academic database, to identify relevant academic articles published over the past 20 years. The reviewed research employed a range of machine learning and DL techniques, including ANN, SVM, GA, LSTM, fuzzy logic (FL), sensitivity analysis, technical analysis, and others, to predict the stock market's future trajectory within the classification sets. Additionally, the researchers employed technical indicators and daily stock prices as inputs to predict future prices. The results of the experiments demonstrated that it is feasible to construct an efficient and effective forecasting model without undertaking complex tasks such as data preprocessing or seasonality testing. In addition to filtering, another prevalent clustering technique is fuzzy logic, which is a computational technique based on accuracy. The most frequently utilized keywords are "stock market prediction," "stock market," "ML," "DL," and "stock market prediction." A total of 220 articles were analyzed, and it was concluded that ANN and fuzzy-based techniques are the most widely adopted forecasting and clustering techniques, respectively.

In a recent study, Gülmez [21] used a deep LSTM network optimized with the Artificial Rabbit Optimization algorithm (ARO) model (LSTM-ARO) to predict stock prices. The dataset comprises stocks from the Dow Jones Industrial Average (DJIA) index. The dataset covers the period from January 1, 2018, to January 1, 2023. The closing price of the subsequent trading day was forecast. Eighty percent of the data was utilized for training purposes, while the remaining twenty percent was reserved for testing. The LSTM-ARO model was evaluated in comparison with an ANN model, three distinct LSTM models, and a GA model. All models were evaluated in accordance with the MSE, MAE, MAPE, and R2 criteria. The results demonstrate that the LSTM-ARO model exhibits superior performance compared to the other models.

Nasiri *et al.,* [22] put forth two innovative methodologies for multi-step stock price prediction. The DCT-MFRFNN method is founded upon the discrete cosine transform (DCT) and the multifunctional recurrent fuzzy neural network (MFRFNN). They employed the DCT to mitigate fluctuations in the time series and streamline its structure, while utilizing the MFRFNN to forecast the stock price. The VMD-MFRFNN approach, which is based on variable mode decomposition (VMD) and MFRFNN, represents a synthesis of the aforementioned methods, combining their respective advantages. VMD-MFRFNN comprises two stages. In the decomposition stage, the input signal is decomposed into a number of intrinsic mode functions (IMFs) using the VMD technique. The efficacy of the proposed methods was evaluated using three financial time series: the Hang Seng Index (HSI), the Shanghai Stock Exchange (SSE), and the Standard & Poor's 500 Index (SPX). The experimental results demonstrate that VMD-MFRFNN exhibits superior performance compared to other state-of-the-art methods.

In a recent study, Zhang *et al.,* [23] proposed a CNN with BiLSTM and attention mechanisms to enhance the precision of stock price and index forecasting. In this study, data encompassing a total of 2,675 trading days of the Shanghai Shenzhen CSI 300 Index from January 4, 2011, to December 31, 2021, were utilized for the purposes of stock price forecasting and closing price prediction. The selected dataset comprises the opening price, high price, low price, closing price, volume, turnover, and return. This method is compared with LSTM, CNN-LSTM, and CNN-LSTM-Attention models. The models are evaluated using three statistical metrics: MAPE, RMSE, and coefficient of determination $R2$. The results demonstrate that the CNN-BiLSTM-Attention model exhibits superior accuracy in predicting stock closing prices, outperforming the other three models.

To enhance the precision of stock price forecasting, Li *et al.,* [24] proposed an advanced deep learning framework with clustering to predict stock prices using three established DL prediction models, namely LSTM, RNN, and Gated Recurrent Unit (GRU). To achieve effective clustering, a new similarity measure, Logistic Weighted Dynamic Time Deviation (LWDTW), is proposed as an extension of the Weighted Dynamic Time Deviation (WDTW) method. The objective is to capture the relative importance of return observations when computing distance matrices. The dataset comprises comprehensive historical daily price and volume data for US stocks listed on the New York Stock Exchange (NYSE), the NASDAQ stock market, and the NYSE MKT (formerly the American Stock Exchange, AMEX). It encompasses opening, high, low, and closing prices, as well as trading volume, for the period between 1970 and 2017. The period from January 2005 to November 2017 was selected for examination of recent trends in stock price movements. The models were evaluated using a series of statistical metrics, including MAPE, MAE, Mean Square Error (MSE), RMSE, and R-squared (R2). The results of the evaluation demonstrate that LWDTW-based cluster forecasting in conjunction with the LSTM model represents the most effective methodology for stock price prediction, exhibiting the lowest MAPE (0.1278), MAE (0.0536), MSE (0.0059), RMSE (0.0745), and the highest average R2.

Kanwal *et al.,* [25] put forth a hybrid DL forecasting model that incorporates Bidirectional Cuda Deep Neural Network Long Short-Term Memory (BiCuDNNLSTM) and one-dimensional Convolutional Neural Network (CNN) for the purpose of achieving timely and efficient forecasting. The proposed model (BiCuDNNLSTM-1dCNN) was evaluated using five stock price datasets and compared with other hybrid DL-based and state-of-the-art models for validation purposes. The models were evaluated using Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) measures. The proposed model, BiCuDNNLSTM-1dCNN, is compared with four other deep learning (DL) models: LSTM-CNN, LSTM-DNN, CuDNNLSTM, and LSTM. The data set comprises three distinct categories: crude oil (30.03.1983-15.08.2018), crude oil (23.08.2000-15.01.2021), and global x dax Germany ETF (23.10.2014-31.12.2020) for individual stock items. Additionally, it includes the Frankfurt Stock Exchange DAX Performance Index (01.01.2000-16.06.2021) and the Hong Kong Stock Exchange Hang Seng Index (01.01.2000-25.06.2021) for stock market performance indices. The experimental results demonstrate that the proposed model, BiCuDNNLSTM-1dCNN, exhibits superior prediction accuracy in comparison to the other four DL models.

In a recent study, Muhammad *et al.,* [26] developed a machine learning model based on the transformer technique to predict the future price of stocks traded on the Dhaka Stock Exchange (DSE), the leading stock exchange in Bangladesh. This study focuses on the application of the transformer-based model to predict the closing price of eight specific stocks listed on the DSE stock exchange using historical daily and weekly data. The data set includes stock data from October 2012 to December 2020, sourced from Amarstock. The data set includes the following variables: trade code, date, opening price, high price, low price, closing price, and volume. The Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) are employed to assess the efficacy of the models. The proposed model is capable of forecasting not only the price after the trading day but also the price one week hence.

Yang *et al.,* [27] sought to enhance the precision of stock price forecasting. The stock trading data, including the opening price, closing price, highest price, lowest price, and trading volume, were parsed using the BeautifulSoup library. The historical data of S&P 500 technology stocks, spanning from January 1, 1990, to December 31, 2020, were utilized, amounting to a total of 30 years. Although SVM is an excellent choice for classification tasks, it may not be the optimal for predicting stock prices, which involve continuous value prediction. Experimental results indicate that SVM performs slightly better than Random Forest but still significantly trails behind deep learning-based models. The Temporal Transformer, which was specifically designed for time series data and integrates traditional time series analysis techniques, outperforms both models.

Chen *et al.,* [28] proposed a vector autoregression (VAR)-based rolling forecast model to predict stock prices and a Gaussian feedforward neural network (GFNN)-based graph signal identification method to recognize different types of stock price signals. Stocks were randomly selected from Yahoo Finance's trading records was employed, with historical data spanning from January 28, 2019, to January 25, 2022. To facilitate a comparative analysis, the TCN, GRU, and LSTM methods were utilized. The efficacy of the model was evaluated using metrics including accuracy (Acc), mean squared error (MSE), and explained variance (Evar), which were calculated using specific equations. The proposed approach demonstrated superior performance compared to the GRU and LSTM methods. While the proposed method demonstrated comparable performance to TCN, it achieved higher accuracy on a greater number of datasets than TCN.

Wang *et al.,* [29] proposed an advanced interval-valued decomposition integration model for stock price prediction. This model is based on comprehensive feature extraction and optimized deep learning. In order to extract internal features and decompose interval values into interval trends and residues, they introduced Feedback Interval Variational Modal Decomposition (FIVMD). This method effectively performs external feature extraction using appropriate feature selection and compression techniques, identifies the most influential factors, and enhances the modeling capability for high-dimensional data. The stock indices used in this study encompass the Shenzhen Stock Exchange Index (SZI), the Shanghai Stock Exchange Composite Index (SSEC), and the China Securities 100 Index (CSI100). The dataset comprised stock data from April 10, 2014, to April 20, 2023. The results showed that the proposed model exhibited superior accuracy and stability compared to other models.

3. Methodology

3.1 Dataset

The dataset utilized in this study encompasses the daily closing prices of the 100 companies listed on the Istanbul Stock Exchange (Bist100) in Turkey, considering their market and transaction volumes, spanning the period from February 2020 to December 2023. From the Bist100, the top 5 companies were selected based on market capitalization, which was calculated by multiplying the price per share by the number of shares outstanding. The research data were sourced from Yahoo Finance. Python was employed to compare the results for price index estimation and to identify the optimal algorithm using deep learning methodologies. The error evaluation criteria included Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Explained Variance Score (EVS), Mean Absolute Percentage Error (MAPE), Median Absolute Deviation (MDA), Mean Squared Logarithmic Error (MSLE), and the Coefficient of Determination (R^2).

3.2 Deep Learning

The foundation of DL algorithms is rooted in the computational modeling of neurons within the human brain. The field of DL has its roots in the work of Donald Hebb on the structure of NN. Subsequently, the construction of a mathematical model within a computer environment represents the inaugural stage of ANN. Since their inception, ANNs have undergone significant advancements. In recent years, the term "deep learning" has emerged as a prominent concept in this field. Moreover, the majority of studies have concentrated on this topic [30]. DL represents a subcategory of ML. DL employs a multitude of non-linear processing units to facilitate feature extraction and transformation. The output of the preceding layer serves as the input for the subsequent layer. In the context of DL, a structure is employed that enables the learning of multiple levels of features or the representation of data [31]. The specific characteristics of ANNs are contingent upon the intended application and context in which they are utilized. The optimal model is contingent upon the nature of the problems at hand. Classification, detection, diagnosis, prediction, and so forth. The selection of an appropriate neural network model is crucial for achieving optimal results. Furthermore, the optimal NN model may vary depending on the intended use of the data. Furthermore, the optimal neural network model can be determined based on the data type, which may be image, sound, or signal [32].

3.3 Artificial neural network

The ANN model was initially developed by Warren McCulloch and Walter Pitts in 1943 [33]. They demonstrated that any logical expression can be formulated using an ANN. In their 1943 publication, McCulloch and Pitts articulated the mathematical theory of neural behavior as follows:

i. A neuron can be driven to emit a signal that can be either on or off.
ii. Neurons possess activation functions.

iii. Upon stimulation of the inputs, the resulting output is received instantaneously.
iv. When the inputs to the neuron are blocked, the stimulation of the neuron is prevented at that moment [33].

The configuration of neuronal networks within the nervous system remains unaltered. Subsequently, Frank Rosenblatt proposed the perceptron, a rudimentary artificial neural network model, in 1957. The perceptron takes the input data and multiplies it by the weights, applies a threshold value, and produces an output. Nevertheless, Rosenblatt's perceptron model is employed for the resolution of relatively straightforward classification issues. ANNs are digitized models of the human brain. They are computer programs designed to simulate the manner in which the human brain processes information. ANNs learn or are trained not through programming but through experience with appropriate learning examples, in a manner analogous to that observed in humans [34].

A neuron in an ANN is composed of a number of different elements. These are the elements in question:

Inputs are defined as the data that are fed into the neuron, which are typically numerical values. Weights are values that are assigned to each input, and they are used to determine the importance of that input in the overall computation performed by the neuron. Bias is defined as a constant value that is added to the weighted sum of the inputs. The activation function is a mathematical function that determines the output of the neuron in dependence on the inputs and weights. The most prevalent activation functions employed in ANN are the softplus, sigmoid, tanh, and ReLU functions. The output represents the final result of the neuron's calculation and is subsequently transmitted to other neurons within the network. The error is defined as the discrepancy between the predicted output of the neuron and the actual output. This is utilized to adjust weights and biases with the objective of enhancing the accuracy of the network [21].

$$y_p = \sum_{i=1}^{n}\left(w_{ji} * x_i\right) + b \tag{1}$$

In the formula 1, the net_i value represents the output signal of neuron i; the w_{ij} variable denotes the synaptic connection between neuron i and neuron j; and the variable x_i signifies the output of neuron j. An input vector (x_i,…, x_n), comprising variables from the existing system, is multiplied by the weight vector (w_1,…, w_p) associated with the neuron. The output of neuron i is equal to the signals originating from neuron j and directed to neuron i, multiplied by the weights and the sum of all products. The term refers to a constant value that is added to the input of the b activation function, which is also known as the bias [35].

3.4 Convolutional neural network

CNN is a DL algorithm that takes images as input and extracts features by filtering or transforming them with kernels [36]. It is employed in a multitude of domains, including image recognition, natural language processing, and time series analysis. The CNN algorithm draws inspiration from the visual centers of animals [37]. The CNN consists of three principal layers: convolutional, pooling, and fully connected. The convolution process may be conceptualized as a neuron's response to stimuli originating from the stimulus field [31]. CNN is a convolutional neural network that employs a feature map to divide an input image into distinct features. It is a process of matrix multiplication, whereby the input image is shifted over using one or more pixels. Pixels are instrumental in defining the characteristics of an image. In its operational methodology, the input features are subjected to periodic scanning, and any discrepancies are incorporated through the addition of the input features and multiplication by the matrix elements within the receptive field [38]. Pixels are related to adjacent and nearby pixels, and thus convolution allows for the preservation of the relationship between different parts of the image. Convolution preserves the relationship between pixels. The objective is to filter the image with a smaller pixel filter, thereby reducing the image's overall size [37]. Equation 2 demonstrates the process of passing the filter matrix for each pixel of the input matrix and multiplying the filter matrix and pixel values element by element.

$$Output(i,j) = max_{m,n} Input(i+m, j+n) \tag{2}$$

$Output(i,j)$, is the element at position (i,j) of the output matrix obtained as a result of the retting process.

$Input(i+m, j+n)$, is the element at position (i+m,j+n) of the input matrix subjected to retting.

$max_{m,n}$, finds the maximum value within a given region.

3.5 Long short-term memory

RNN has short-term memory. Therefore, if the network is long, it will be difficult to move information to the next network. When prediction is made in the network, RNN may exclude some of the information. LSTM provides a suitable solution to the problems of vanishing and exploding gradients of RNNs that occur when analyzing large data sets with RNN. Gradients are values used to update the weights of the neural network. Backpropagation travels from the output back to the input layer, propagating the error gradient. The vanishing gradient problem is that the gradient gets smaller over time as it propagates backward. If the gradient value is too small, it will not contribute much to learning. In RNN, layers that receive gradient updates stop learning. Those that contribute less to learning are usually the more advanced layers. Since these layers do not learn, RNNs can forget what they see in longer sequences. Therefore, they have short-term memory [23].

As one progresses from higher-level to lower-level layers, trends tend to become less pronounced. This phenomenon is particularly evident at the input layers, which are situated at the forefront of the network. Consequently, the weights of the neurons remain constant at these lower levels. Activation functions or batch normalization techniques may be proposed as potential solutions to the issue of gradients vanishing at a certain scale. However, the length of the sequence input, such as that of long time series data, may result in a reduction in the efficiency of the training process. As information is lost with each step that passes through the RNN, the network will eventually forget the initial inputs. It is therefore necessary to develop a long-term memory solution for RNN. The LSTM cell was developed in 1997 with the objective of addressing the vanishing gradient problem [39]. The LSTM architecture comprises an input layer, a forget layer, an output layer, a block input layer, a fixed failure loop, an output activation function, and peephole connections [31]. LSTMs comprise four layers that interact with one another to generate an output. These layers include three logistic sigmoid gates and one tanh layer. The function of the gates is to restrict the flow of information through the cell. The subsequent cell is responsible for determining which portion of the information will be retained and which will be discarded. The gate mechanisms in LSTMs are employed to update the contents of memory cells and determine the quantity of information to be retained and that to be discarded. These gates are designated as "forget," "update," and "exit" gates, respectively, and each is regulated by a sigmoid activation function. The structure of LSTMs enables them to accurately recall past information and learn long-term dependencies with precision [40].

3.5 Bidirectional Long short-term memory

Bidirectional RNN, developed by Schuster and Paliwal, is a type of RNN designed to train the network using past and future input data sequences. This structure is used especially in speech processing and time series analysis. BiLSTM is an improved version of this approach and aims to achieve the best learning performance by using all data. BiLSTM is based on the BiLSTM model, which includes previous and next input sequences. It has been able to overcome the vanishing gradient problem [41]. The BiLSTM eliminates the single-step truncation present in the LSTM and implements full error gradient computation. The error gradient approach facilitates the implementation of bidirectional LSTM [42]. In addition, it can learn the optimal amount of contextual information relevant to the classification task [41]. An LSTM layer consists of repeatedly connected memory blocks, each containing one or more memory cells, and input, output, and forget gates, called multiplicative gates. The gates perform read, write, and reset operations [42]. Each layer performs operations using the reverse time step direction [41].

4. Results

The data set was selected in accordance with the market capitalization value of the stock traded on Bist100. The term "market cap" is used to describe the total market value of a company or asset. Table 1 illustrates the market capitalization values of the five companies with the highest market capitalization values of the stocks traded on BIST-100. These companies are Koç Holding, Turkish Airlines, Ford Otosan, Türkiye Petrol Rafinerileri, and İş Bankası. The data set utilized for stock estimation in the examined studies is restricted to a specific temporal period.
The stocks selected for the research were considered, and the objective was to estimate the closing value and compare the performance of the models. The model data was designed with a 70% training and 30% test set, and the mean square error (MSE) was employed as the loss function.

Table 1
The market capitalization values

Stocks	MarketCap (1/1000000000 TL)	Industry
KCHOL.IS	443.3900	Conglomerates
THYAO.IS	389.5000	Airlines
FROTO.IS	344.5900	Auto Manufacturers
TUPRS.IS	324.8600	Oil & Gas Refining & Marketing
ISCTR.IS	304.3800	Banks - Regional

The most fundamental technical indicators were selected from the Table 2 in accordance with the data obtained from the literature review. The application of technical indicators facilitates the extraction of more

meaningful information by reducing the influence of noise in the normalized data. The correlation values between the closing prices and the various subcategories of the technical indicators for stocks were calculated. In the aforementioned section on data information, indicators with a value of 0.80 or above were selected for use in closing price estimation for technical indicators. Consequently, the application of technical indicators facilitated the generation of more meaningful and predictable patterns by attenuating the influence of extraneous data.

Table 2
Technical Indicators

Technical Indicators	
Cumulative Log Return	CUMLOGRET_1
Exponential Moving Average	EMA_8
Simple Moving Average	SMA_8
MACD Moving Average Convergence Divergence	MACD_8_21_9
	MACDh_8_21_9
	MACDs_8_21_9
FWMA Fibonacci's Weighted Moving Average	FWMA_8
Bollinger Bands: bbands	BBL_5_2.0
	BBM_5_2.0
	BBU_5_2.0
	BBB_5_2.0
	BBP_5_2.0
Stochastic RSI: stochrsi	STOCHRSIk_14_14_3_3
	STOCHRSId_14_14_3_3
Stochastic Oscillator: stoch	STOCHk_14_3_3
	STOCHd_14_3_3
Momentum: mom	MOM_10
Ichimoku Kinkō Hyō: ichimoku	ISA_9
	ISB_26
	ITS_9
	IKS_26
	ICS_26
KDJ	K_9_3
	D_9_3
	J_9_3

In Table 3, hyperparameter settings are established for the single-layer LSTM model. Initially, the number of layers and the number of neurons in each layer are determined. Common choices for the number of neurons per layer include 32, 64, and 128; in our model, we selected 64 neurons. Subsequently, the activation functions for each layer are chosen, with 'relu', 'sigmoid', and 'tanh' being the most preferred in this study, we selected relu function.

The input data is then passed through the network layers, where it is multiplied by the weights in each layer and passed through the respective activation functions. The error value, calculated as the difference between the real and estimated outputs, is determined. This error is used to update the weights. The backpropagation algorithm optimizes the weights and biases to minimize the error rate [43].

The learning rate, set to 0.001, is crucial in updating the model's weights. This parameter is chosen to prevent the model from overfitting, which can occur with a very high learning rate. The next setting involves determining the batch size, which defines how many examples the model will be updated on during each iteration. Given the typically large size of the training dataset, the batch size divides the training process into smaller groups instead of processing the entire dataset at once. Common batch sizes are 8, 32, 64, and 128; in our model, we selected a batch size of 8.

The learning rate is a hyperparameter that determines the step size at each iteration while moving toward a minimum of the loss function. Model performance is observed by experimenting with different learning rates to find an optimal value. After setting the hyperparameters, the Adam algorithm and other optimization techniques are employed during model training. The Adam (Adaptive Moment Estimation) optimization algorithm is widely used in deep learning and artificial neural network (ANN) training. It updates the model's parameters using the specified hyperparameters and optimizes the learning process. In optimization algorithms, "step size" is obtained by multiplying the gradient by the learning rate, as determined by the gradient descent algorithm. A low step size means that the gradient will be updated less with each iteration.

Table 3
Single hidden Layer LSTM

First hidden Layer LSTM	
Neuron	64
Activation Function	relu
Optimizer	adam
Obj Function	mse
Epochs	100
Batch Size	8
Learning Rate	0.001
Step Size	8

Table 4
The three-layer long short-term memory

	First Hidden Layer LSTM	Second Hidden Layer LSTM	Third Hidden Layer LSTM
Number Of Neurons	64	128	128
Activation Function	Relu	Tanh	Tanh
Optimizer		Adam	
Obj Function		Mse	
Epochs		100	
Batch Size		8	
Learning Rate		0.001	
Step Size		8	

In Table 4, the number of neurons in the second layer and the number of neurons in the third layer in the three-layer long short-term memory (LSTM) method was determined to be 128. The activation function employed in these layers was Tanh. Once the training of the model is complete, the prediction step is initiated using the test data. A variety of measurement metrics have been employed to assess the model's performance error.

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Table 5
The three-layer bidirectional long short-term memory

	First Hidden Layer (Bidirectional)	Second Hidden Layer (Bidirectional)	Third Hidden Layer (Bidirectional)
Neuron	64	128	128
Activation Function	Relu	Tanh	Tanh
Optimizer	Adam		
Obj Function	Mse		
Epochs	100		
Batch Size	8		
Learning Rate	0.001		
Step Size	8		

In Table 5, the number of neurons in the second layer and the number of neurons in the third layer in the three-layer bidirectional long short-term memory (BiLSTM) method was determined to be 128. In these layers, the activation function was Tanh.

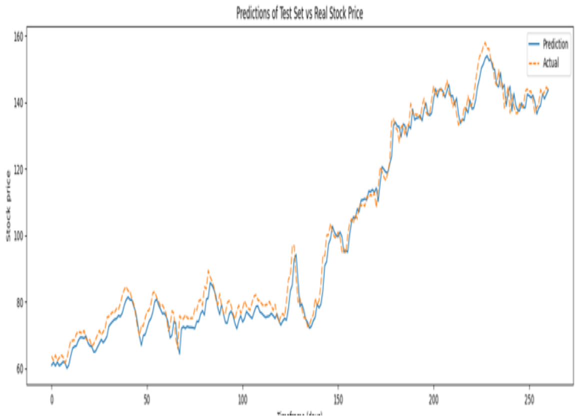

Fig. 1. Plot for Real value vs Predicted value for KCHOL.IS using BiLSTM

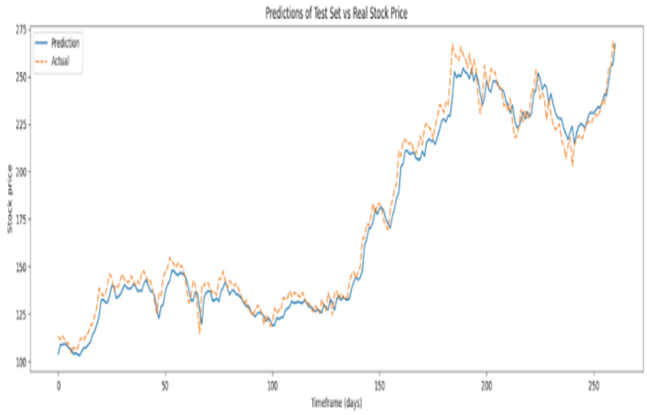

Fig. 2. Plot for Real value vs Predicted value for THYAO.IS using BiLST

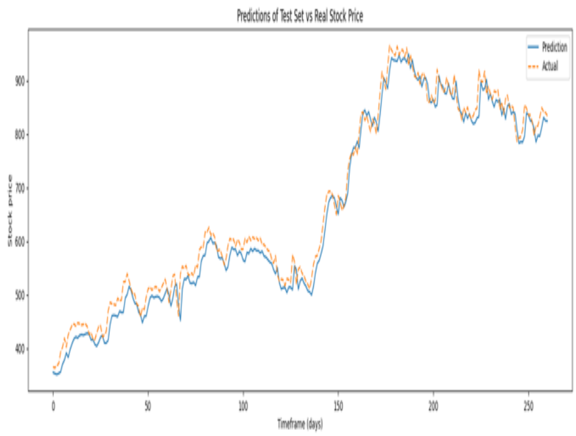

Fig. 3.Plot for Real value vs Predicted value for FROTO.IS using BiLSTM

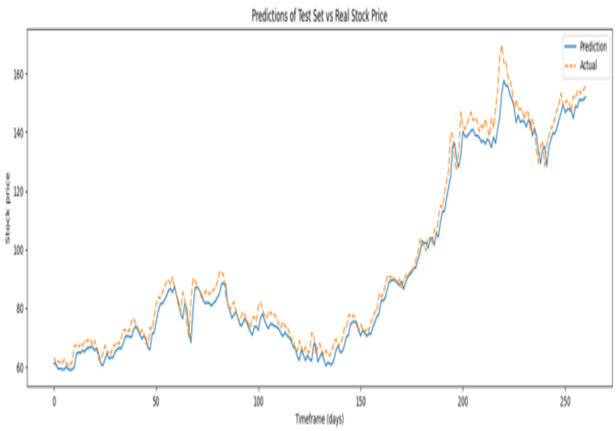

Fig. 4. Plot for Real value vs Predicted value for TUPRS.ISusingBiLSTM

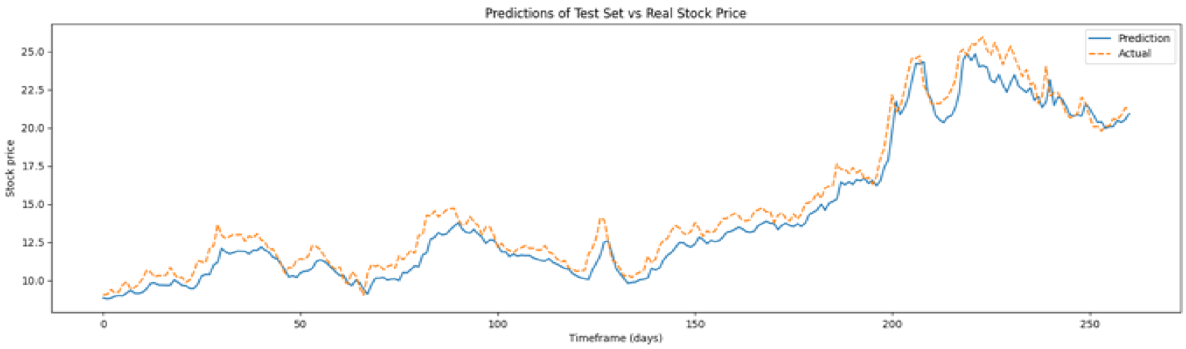

Fig. 5. Plot for Real value vs Predicted value for ISCTR.IS using BiLSTM

The following section presents the application of the proposed BiLSTM model for forecasting the future price trajectory of KCHOL.IS, THYAO.IS, FROTO.IS, TUPRS.IS, and ISCTR.IS shares, based on historical data. The abscissa represents the number of days, while the ordinate depicts the share price. Upon plotting the estimated test price (blue) and the actual price (red), it becomes evident that there is a negligible discrepancy between the two. The data from the 250-day interval are presented in Figures 1, 2, 3, 4, and 5. As illustrated in Figures 1, 2, and 3, the BiLSTM method demonstrates the capacity to discern the shifts in trend over the 200-to-250-day interval. However, as illustrated in Figures 4 and 5, the network demonstrates less success in capturing trends and dynamics within the time period between 200 and 250.

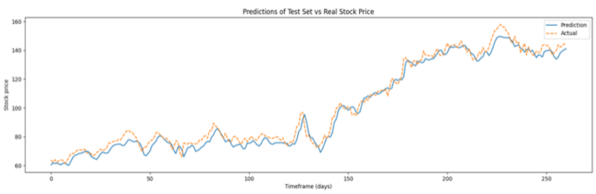

Fig. 6. Plot for Real value vs Predicted value for KCHOL.IS using CNN-LSTM

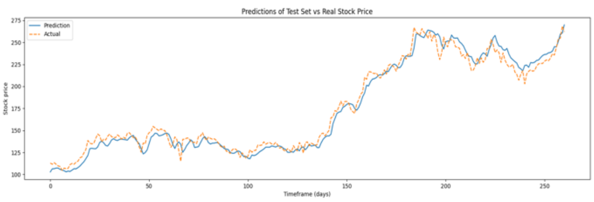

Fig. 7. Plot for Real value vs Predicted value for THYAO.IS using CNN-LSTM

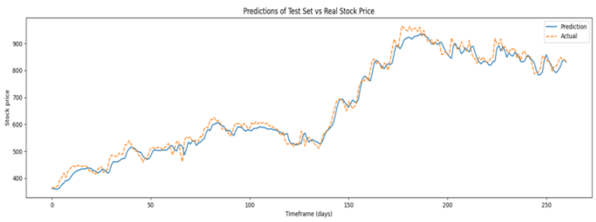

Fig. 8. Plot for Real value vs Predicted value for FROTO.IS using CNN-LSTM

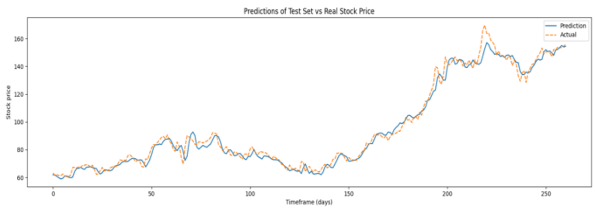

Fig. 9. Plot for Real value vs Predicted value for TUPRS.IS using CNN-LSTM

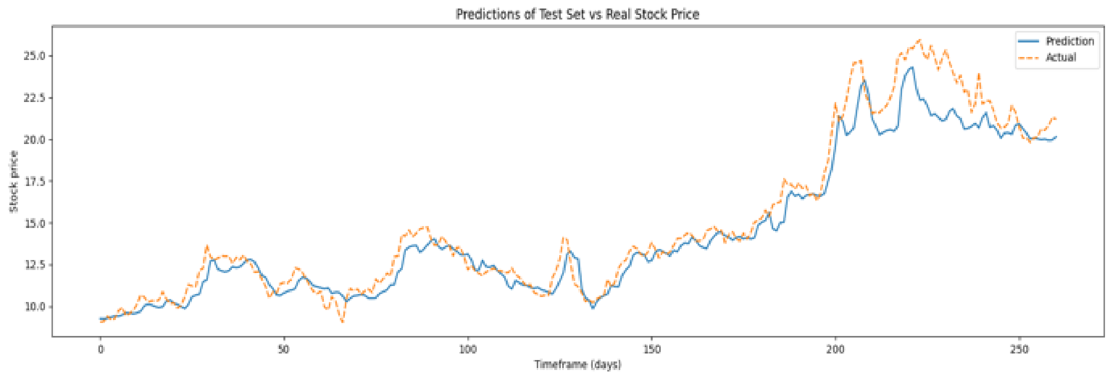

Fig. 10. Plot for Real value vs Predicted value for ISCTR.IS using CNN-LSTM

A prediction was made regarding the future price of KCHOL.IS, THYAO.IS, FROTO.IS, TUPRS.IS, and ISCTR.IS shares, based on an analysis of historical data. The resulting stock price prediction graph, which illustrates the performance of the CNN-LSTM model, is presented in the figure below. The abscissa represents the number of days, while the ordinate depicts the share price. The algorithm has been successfully plotted with the predicted test price (blue) and the actual price (red). In the aggregate, the discrepancy between the estimated test price (blue) and the actual price (red) is minimal. The data presented in Fig. 6, Fig. 7, Fig. 8, Fig. 9, and Fig. 10 span a 250-day interval. As illustrated in Figures 6, 7, 8 and 9, the CNN-LSTM method demonstrates the capacity to discern shifts in trend over time intervals between 200 and 250. However, Fig. 10 illustrates that the network did not demonstrate the same degree of success in identifying trends and dynamics within the 200-250 time period.

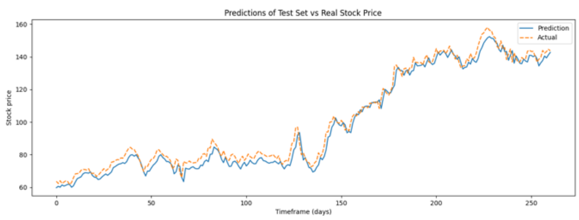

Fig. 11. Plot for Real value vs Predicted value for KCHOL.IS using Three-Layer LSTM

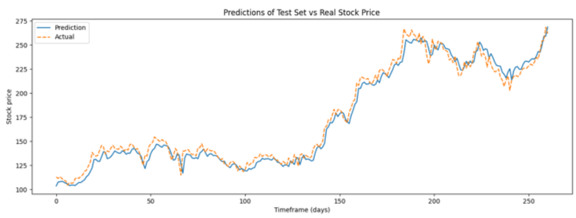

Fig. 12. Plot for Real value vs Predicted value for THYAO.IS using Three-Layer LSTM

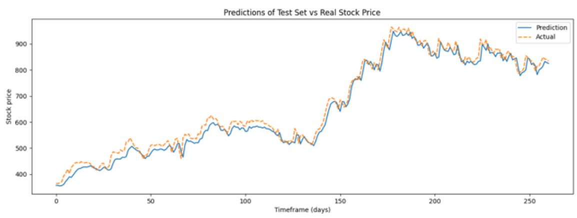

Fig. 13. Plot for Real value vs Predicted value for FROTO.IS using Three-Layer LSTM

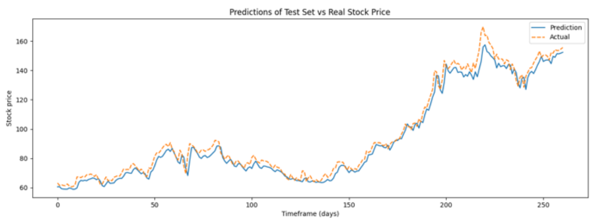

Fig. 14. Plot for Real value vs Predicted value for TUPRS.IS using Three-Layer LSTM

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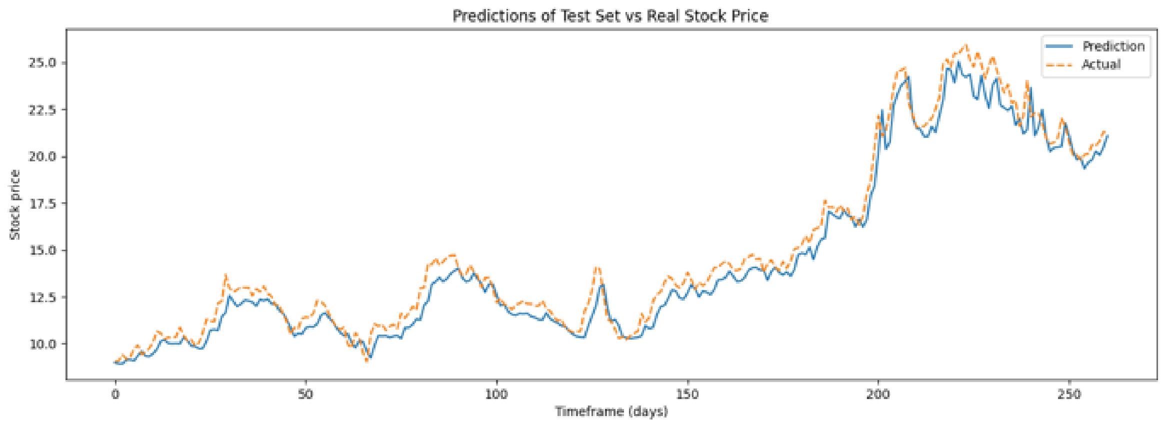

Fig. 15. Plot for Real value vs Predicted value for ISCTR.IS using Three-Layer LSTM

A prediction was made regarding the future price of KCHOL.IS, THYAO.IS, FROTO.IS, TUPRS.IS, and ISCTR.IS shares, based on an analysis of historical data. The resulting stock price prediction graph, which illustrates the performance of the 3L-LSTM model, is presented in the figure below. The abscissa represents the number of days, while the ordinate denotes the share price. The algorithm has been successfully plotted with the predicted test price (blue) and the actual price (red). In the aggregate, the discrepancy between the estimated test price (blue) and the actual price (red) is minimal. The data presented in Fig. 11, 12, 13, 14, and 15 represent a 250-day interval. The 3L-LSTM method demonstrates clear ability to capture trends and dynamics throughout the examined time period, as well as to identify and represent changes in trend.

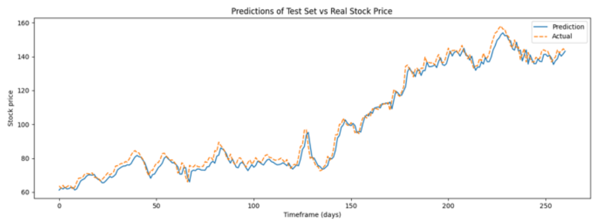

Fig. 16. Plot for Real value vs Predicted value for KCHOL.IS using SingleLayer-LSTM

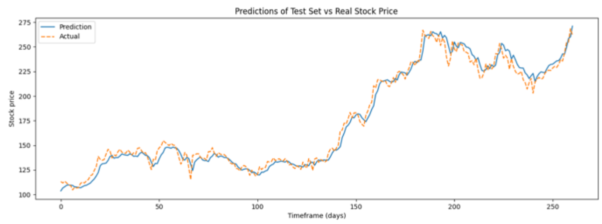

Fig. 17. Plot for Real value vs Predicted value for THYAO.IS using SingleLayer-LSTM

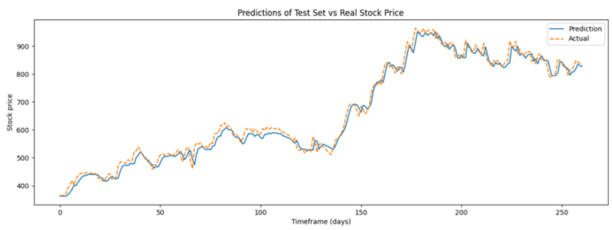

Fig. 18. Plot for Real value vs Predicted value for FROTO.IS using SingleLayer-LSTM

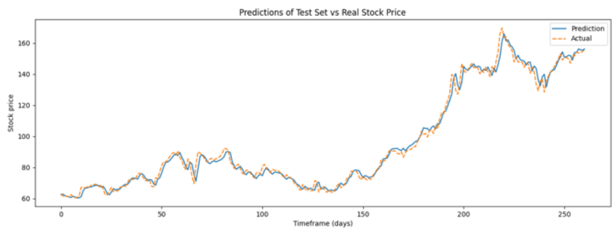

Fig. 19. Plot for Real value vs Predicted value for TUPRS.IS using SingleLayer-LSTM

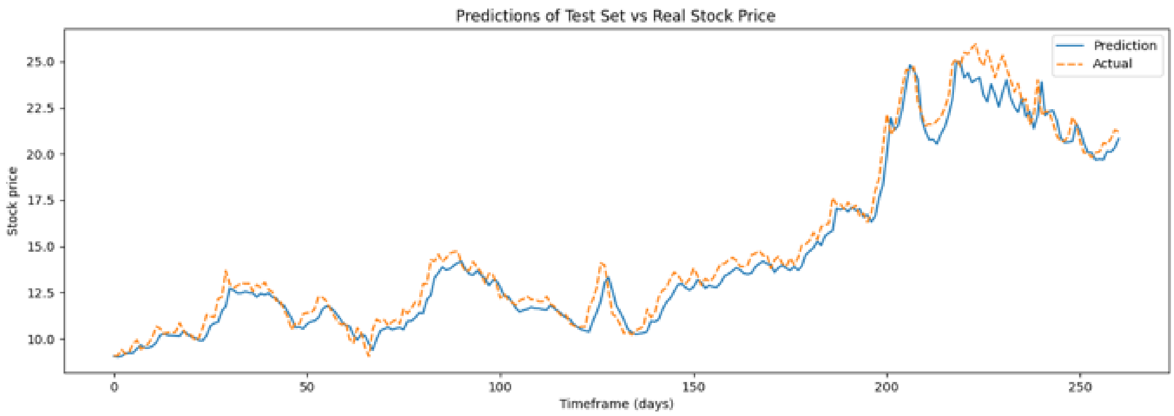

Fig. 20. Plot for Real value vs Predicted value for ISCTR.IS using SingleLayer-LSTM

A prediction was made regarding the future price of KCHOL.IS, THYAO.IS, FROTO.IS, TUPRS.IS, and ISCTR.IS shares, based on an analysis of historical data. The figure presents a stock price prediction graph illustrating the performance of the Single Layer-LSTM model. The abscissa represents the number of days, while the ordinate denotes the share price. The algorithm has been successfully plotted with the predicted test price (blue) and the actual price (red). In the aggregate, the discrepancy between the estimated test price (blue) and the actual price (red) is minimal. The data presented in Fig. 16, 17, 18, 19 and 20 represent a 250-day interval. As illustrated in Figures 16, 17, 18, 19 the Single Layer-LSTM method demonstrates the capacity to discern and replicate the fluctuations in the trend over the specified time interval, spanning 200 to 250 days. However, the network depicted in Figure 20 was unable to achieve the same degree of success in capturing trends and dynamics within the specified time period between 200 and 250.

Table 6
Summary of results obtained for the close price of Bist100

FROTO.IS	EVS	MAE	MAPE	MDA	MSE	MSLE	RMSE	r2_score	CPUtime
Single Layer-LSTM	0,9884	0,0205	0,0482	0,5320	0,0007	0,0003	0,0266	0,9865	22,6202
Three-Layer LSTM	0,9881	0,0259	0,0638	0,5312	0,0010	0,0005	0,0317	0,9808	69,1803
Single Layer BiLSTM	0,9877	0,0261	0,0665	0,5305	0,0010	0,0005	0,0320	0,9804	111,8846
CNN-LSTM	0,9854	0,0234	0,0557	0,5316	0,0009	0,0004	0,0304	0,9824	60,8400
ISCTR.IS	EVS	MAE	MAPE	MDA	MSE	MSLE	RMSE	r2_score	CPUtime
Single Layer-LSTM	0,9815	0,0279	0,0796	0,4927	0,0013	0,0006	0,0362	0,9729	22,4726
Three-Layer LSTM	0,9832	0,0307	0,0888	0,4927	0,0015	0,0007	0,0386	0,9692	68,0938
Single Layer BiLSTM	0,9808	0,0386	0,1160	0,4906	0,0022	0,0011	0,0466	0,9552	113,6686
CNN-LSTM	0,9548	0,0375	0,0954	0,4925	0,0030	0,0012	0,0545	0,9386	45,2971
KCHOL.IS	EVS	MAE	MAPE	MDA	MSE	MSLE	RMSE	r2_score	CPUtime
Single Layer-LSTM	0,9903	0,0209	0,0542	0,5179	0,0007	0,0003	0,0265	0,9868	23,0434
Three-Layer LSTM	0,9895	0,0260	0,0718	0,5151	0,0010	0,0005	0,0316	0,9811	67,2800
Single Layer BiLSTM	0,9891	0,0222	0,0611	0,5163	0,0008	0,0004	0,0277	0,9856	122,9685
CNN-LSTM	0,9864	0,0264	0,0721	0,5162	0,0011	0,0005	0,0327	0,9799	45,5374
THYAO.IS	EVS	MAE	MAPE	MDA	MSE	MSLE	RMSE	r2_score	CPUtime
Single Layer-LSTM	0,9819	0,0240	0,0602	0,5248	0,0010	0,0004	0,0311	0,9818	22,4991
Three-Layer LSTM	0,9815	0,0264	0,0674	0,5263	0,0011	0,0005	0,0333	0,9792	67,5548
Single Layer BiLSTM	0,9825	0,0264	0,0662	0,5264	0,0011	0,0005	0,0336	0,9788	116,9388
CNN-LSTM	0,9751	0,0297	0,0757	0,5255	0,0014	0,0006	0,0368	0,9746	48,8059

TUPRS.IS	EVS	MAE	MAPE	MDA	MSE	MSLE	RMSE	r2_score	CPUtime
Single Layer-LSTM	0,9886	0,0165	0,0458	0,4967	0,0005	0,0002	0,0231	0,9886	22,4607
Three-Layer LSTM	0,9880	0,0244	0,0676	0,4973	0,0010	0,0005	0,0317	0,9785	68,2111
Single Layer BiLSTM	0,9884	0,0240	0,0681	0,4979	0,0010	0,0004	0,0309	0,9795	116,3628
CNN-LSTM	0,9843	0,0201	0,0578	0,4971	0,0008	0,0004	0,0281	0,9831	43,8241

Performance evaluation metrics are employed to assess the accuracy and efficacy of output values derived from input values within a given model. The values of the performance evaluation metrics and CPU time values for each model considered in the thesis are provided in the following table 6. A lower MSE (mean square error) value indicates a superior model performance. As evidenced by the stocks FROTO.IS, ISCTR.IS, KCHOL.IS, THYAO.IS, and TUPRS.IS, the most optimal model is the single-layer LSTM method. A lower MAPE indicates a superior model. The Single Layer LSTM method yielded the optimal MAPE result when evaluated using the FROTO.IS, ISCTR.IS, KCHOL.IS, THYAO.IS, and TUPRS.IS stocks. The coefficient of determination (R^2) is a measure of how well the model fits the data. A value of 1 indicates an optimal model (Chen, 2021). As evidenced by the stocks FROTO.IS, ISCTR.IS, KCHOL.IS, THYAO.IS, and TUPRS.IS, the optimal model is the single-layer LSTM method.

Studies comparing different deep learning algorithms have been examined in the literature. Similar to this study, different machine algorithms were used, but no study was found that paid more attention to pre-processing to normalize the data. The results obtained in the findings section provide useful advice for investors. Among the deep learning models, the single-layer LSTM, three-layer LSTM, three-layer BiLSTM, and CNN-LSTM methods were employed.

5. Conclusion

The task of predicting stock prices is inherently challenging due to the dynamic, non-linear, complex, non-parametric, and chaotic nature of the stock market. Stock market movements are influenced by a multitude of macroeconomic factors, including political events, corporate policies, and prevailing economic conditions. In this sector, it is not always feasible to obtain realistic predictions due to the non-linearity of the data. Consequently, developing AI systems for such predictions necessitates an iterative process of knowledge discovery and system improvement through data mining, knowledge engineering, theoretical and data-driven modeling, as well as trial and error experiments. The primary objective of investors is to attempt to anticipate future stock prices or returns. It is often the case that a single method is insufficient. Consequently, more comprehensive predictions are made by combining multiple analyses. Given the numerous external factors that influence stock forecasting, it is crucial to implement a robust risk management strategy to navigate these uncertainties. This is why a variety of analytical techniques and methods are employed for prediction purposes. In this study, the shares of KCHOL.IS, THYAO.IS, FROTO.IS, TUPRS.IS, and ISCTR.IS, which are among the five largest companies in the BIST100 index according to market capitalization, were selected for analysis. Initially, it was hypothesized that utilizing raw data for stock price prediction would result in a lower success rate. In order to prevent the models from negatively affecting the learning process and reducing the prediction performance, technical indicators were calculated without the use of the data directly for prediction. This approach yielded more meaningful and descriptive features. Among the models recommended for each stock, the least error is observed in the MSE, RMSE, and R2 metrics when compared to the other three models for single-layer LSTM. Furthermore, the least favorable outcomes were observed in the single-layer CNN-LSTM methods for KCHOL.IS, THYAO.IS, and ISCTR.IS stocks, and in the single-layer BiLSTM models for FROTO.IS and TUPRS.IS stocks. It has been demonstrated that predictions can be made using historical data.

The application of sophisticated analytical techniques in the financial sector enables investors to enhance risk management and make more informed strategic decisions. Further research in this field may establish new benchmarks for market analysis, enhancing the precision and dependability of financial modeling.

Author Contributions

Conceptualization, M.K., M.G., and A.T.D.; methodology, A.T.D.; investigation, M.G., and A.T.D.; resources, M.K.; writing—original draft preparation, M.G., and A.T.D.; writing—review and editing, M.G. and M.K.; visualization, A.T.D.; supervision, A.T.D.; All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

Data will be made available on request.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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