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RESEARCH PAPER

# Price prediction of dual-listed stocks with RF and LSTM algorithms: NYSE and BIST comparison

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## Abstract

Companies are looking for ways to access capital from developed markets instead of local markets to find financing. While some companies use debt instruments for this purpose, others use equity financing methods. One of the techniques used in equity financing is the simultaneous registration of shares on national and foreign stock exchanges, also known as the dual-registration method. Investors entering international markets by investing in dual-registered shares is important for companies to gain capital. However, another important issue for those investing in stocks is the ability to gain capital through accurate prediction of price movements. The aim of this study is to predict the prices of Turkcell stocks traded on Borsa Istanbul and the New York Stock Exchange (NYSE) using machine learning and deep learning methodologies. The results of the analyses conducted with the Random Forest Regressor and Long Short-Term Memory algorithms, which are machine learning and deep learning algorithms, respectively, showed that both algorithms exhibited a lower error rate in predicting the closing prices of Turkcell stocks on the NYSE.

**Keywords**: Dual-listed stocks; LSTM; price prediction; artificial intelligence algorithms

**AMS 2020 Classification**: 60G25; 68T07

## 1 Introduction

The act of being traded on two different stock exchanges has the effect of reducing the cost of capital and increasing the return on investment. In particular, in countries where capital markets

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are not yet fully developed and there is a paucity of savings, companies seek to diversify their capital base by registering for a second time on the stock exchanges of countries where capital markets are more advanced. It is evident that multinational corporations occupy a significant position within the global economy. It has been asserted that companies that register in two different stock exchanges simultaneously enhance their reputation and secure capital under more favourable conditions than those available in national capital markets [1].

In Turkey, a number of stocks have been dual-registered over time. It has been observed that these stocks are predominantly registered in over-the-counter (OTC) markets, as opposed to Borsa Istanbul. However, shares of Turkcell iletisim Hizmetleri A.Ş. are traded on two distinct organised markets: Borsa Istanbul and the New York Stock Exchange (NYSE). As of year-end 2024, Turkcell's market capitalization on Borsa Istanbul was approximately TRY 214 billion. This value indicates that Turkcell's weight in the Borsa Istanbul 100 (BIST 100) index is 4.03%. In addition, the weight of Turkcell stock in the total market capitalization of Borsa Istanbul was determined to be 0.07%. In addition, the total number of Turkcell's shares traded on Borsa Istanbul (BIST) is stated as 2.2 billion shares [2, 3]. For the same period, Turkcell's market capitalization as represented on the NYSE is around USD 5.99 billion [4–6]. In addition, Turkcell's overall weight on the NYSE is 0.03%. 81.4% of Turkcell's market capitalization is represented on the NYSE, while 18.6% is represented on the BIST [2–5]. By 2024, Turkcell's market capitalisation on the New York Stock Exchange (NYSE) is estimated at approximately USD 5.99 billion. In the same year, the total market size of the US telecommunications sector was estimated at approximately USD 1.16 trillion. In light of this data, Turkcell's percentage weight in the telecommunications sector on the NYSE is determined as 0.52%.

From the perspective of those who provide investment capital, there are a number of advantages associated with investing in equities. Furthermore, the equities market's high liquidity enhances these assets' appeal. Nevertheless, investors must be able to accurately predict stock prices in order to make informed decisions regarding purchases and sales. In addition to the numerous conventional techniques employed for this purpose, the recent surge in popularity of artificial intelligence (AI) applications has also garnered significant interest.

In the existing literature on dual-listed stocks, the majority of studies focus on the volatility interaction in stock prices or the effect of the price in one exchange on the price in the other exchange. The objective of this study is to predict the price movements of Turkcell stock, which is traded on two different organised markets, using machine learning and deep learning algorithms, and to ascertain which stock market is better predicted by which algorithm.

As a result of the findings obtained from the study, it is expected to reveal the effectiveness of different algorithms in predicting price movements in dual-listed stocks. This will help investors to make more rational and data-driven decisions. In particular, determining which stock market is predicted with higher accuracy by which algorithm will provide critical information for investors' strategic portfolio management processes. Moreover, for market regulators and policymakers, the findings on the effects of machine learning and deep learning algorithms on price discovery and market efficiency may shed light on policy development processes to improve cross-market dynamics. Thus, while the study is expected to make a significant contribution to the academic literature, it is also expected to have a broad impact on practical applications and policy development for market actors.

## Dual-listed stocks

Stock markets have been formed with the aim of combining investments that are too small to have an added value for the companies and creating resources for those in need of funds and thus strengthening their capital structures. With stock markets, companies undertake the role of both finding equity capital sources and ensuring the efficiency of resource allocation. Companies can spread both their profits and capital to the bottom through the purchase of stocks by savers [7, 8].

One of the most effective methods used by globalised companies to finance their investments is the use of capital markets as a means of supply. The reduction of economic restrictions between countries and the globalisation of these capital markets intensify the competition in these markets. Companies take advantage of this competition and list their shares in different markets in order to attract international investor base and benefit from lower capital costs [1, 9, 10]. Especially for companies in developing countries, listing their shares on stock exchanges in developed countries is very attractive [9, 11–13].

One of the methods preferred by companies traded on national stock exchanges to obtain equity capital from international stock exchanges is called dual registration [1, 9, 10]. Dual-listed is defined as the registration of a company's shares, including its subsidiaries, on the stock exchanges of at least two countries. Dual-listed is a registration method that appears to be two different legal entities while being traded on two different stock exchanges, but actually consists of one company with different characteristics. The reason for this seeming structure of two different companies is the requirement to prepare financial statements in accordance with the legislation of the relevant country. Although they have the same cash flow, the shares of these companies are traded at different prices on the stock exchanges. The reason for this is associated with arbitrage, regulatory requirements, peer movements, market cycles and macroeconomic movements [1, 14]. This regulatory nuance is echoed in other market dynamics, where external variables, such as oil prices or macroeconomic factors, significantly impact stock performances, underlining the complexity of operating across diverse financial ecosystems [15].

From a broad perspective, it can be argued that dual-listed stocks have many benefits. The first of these benefits is that it provides an opportunity to analyse the effects of structural changes of multiple trade [10]. Secondly, it offers companies the chance to obtain the equity capital they need from different areas [1]. It has also been found that the bid-ask spread is lower for dual-listed stocks, given that dual-listed stocks have more trading demand and are part of the portfolios of a larger portfolio manager base compared to local stocks [10, 16–19]. Due to such positive values, in recent years, developed and emerging financial markets have witnessed an increasing trend towards dual-listed and traded stocks [20].

## Machine learning and deep learning

Machine learning is defined as the capacity to learn from problem-specific training data while automating the process of building analytical models to solve relevant tasks in a data-driven manner [21]. Machine learning is the field of study for the application of iterative learning algorithms that give computers the ability to learn from patterns and relationships in data without explicit programming [22, 23]. Machine learning provides good performance in decision tasks related to high-volume data such as classification, regression and clustering. It helps to make reliable and repeatable decisions by learning from previous calculations to extract intrinsic patterns from databases. For this purpose, data mining algorithms and machine learning algorithms have been successfully applied in many areas such as image and speech recognition, natural language processing, fraud detection, customer credit score calculation, retail sales forecasting and the next best price/campaign offer for customers [24]. Furthermore, machine learning techniques have demonstrated superior performance in financial time series forecasting by effectively capturing complex relationships that traditional statistical models often fail to address. This enhanced capability allows machine learning models to provide more accurate and actionable insights for

decision-making in dynamic and high-variance environments [25].
Machine learning algorithms can be classified in many different ways according to their intended use and computational methods. Machine learning algorithms can be classified as follows [23];

- Supervised learning
- Unsupervised learning
- Semi-supervised learning
- Reinforcement learning
- Multi-task learning
- Community learning
- Artificial Neural Networks
- Example-based learning

The relationship between machine learning and deep learning can be illustrated by the following venn- scheme; Source: [21, 26]

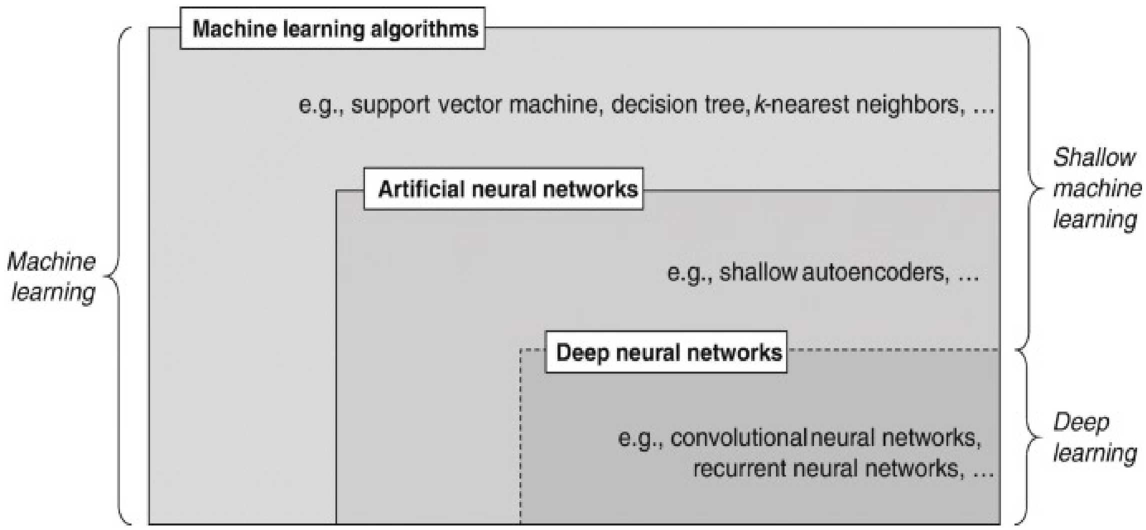


**Figure 1.** Machine learning and deep learning

Machine learning is a general name for methods that automatically reveal patterns in data sets. Deep learning can be called machine learning methods that use the computational methods of Artificial Neural Network algorithms from machine learning methods. Artificial neural networks consist of mathematical formations of interconnected processing units called artificial neurons based on the principles of information processing in biological systems. When the information processing process in the living brain is examined, it is processed sequentially by sending signals that can be increased or decreased between interconnected neurons. Based on this logic, Artificial Neural Network algorithms help to make the best decision by processing the preliminary information in its own mathematical form and then directing it to the next network [22]. Simple Artificial Neural Networks or other machine learning algorithms (decision trees etc.) usually use a simple activation code.
The machine learning algorithm that is appropriate for the purpose of the study is Random Forest Regressor (RF). RF classifier is a supervised learning algorithm. It can be used for both classification and regression. It also has a flexible and easy-to-use algorithm. Random forests create decision trees in randomly selected data samples, make predictions from each tree [27] and the average of the results produced by all trees is returned as the prediction value.
Deep learning or deep neural networks, by performing calculations with multiple activation

codes, allow decisions to be made at a size and stage that cannot be calculated and interpreted by humans. For this reason, Artificial Neural Networks can be called 'Shallow Machine Learning', while neural networks that can calculate patterns that the human brain cannot calculate and reveal are called 'Deep Neural Networks' [28].
Deep Neural Network architectures can be classified as follows [21];

- Convolutional Neural Network (CNN)
- Recurrent Neural Network (RNN)
- Distributed Representation
- Auto Encoder
- Generative Adversarial Neural Network (GAN)

Although every architecture in Deep Learning algorithms can be used for every task, some deep neural network algorithms can give better results for time series data or image data. Deep Neural Network architectures are mostly classified according to the layer type, neural unit and the connections they use [29].
Time series data are data that record the time-dependent change of problem data such as financial data, sensor data, vibration data, weather data. Time series [30];

- Random regular data that has no order,
- Exponentially increasing data over time,
- Data that increases linearly with time,
- Data with a seasonal pattern,
- It can be categorised as time series with a mixture of linear and seasonal patterns.

Time series can be modelled as Ut =Tt+St+Ct+Rt+Rt. Here; Tt: trend, St: seasonality, Ct: periodic, Rt: residuals.

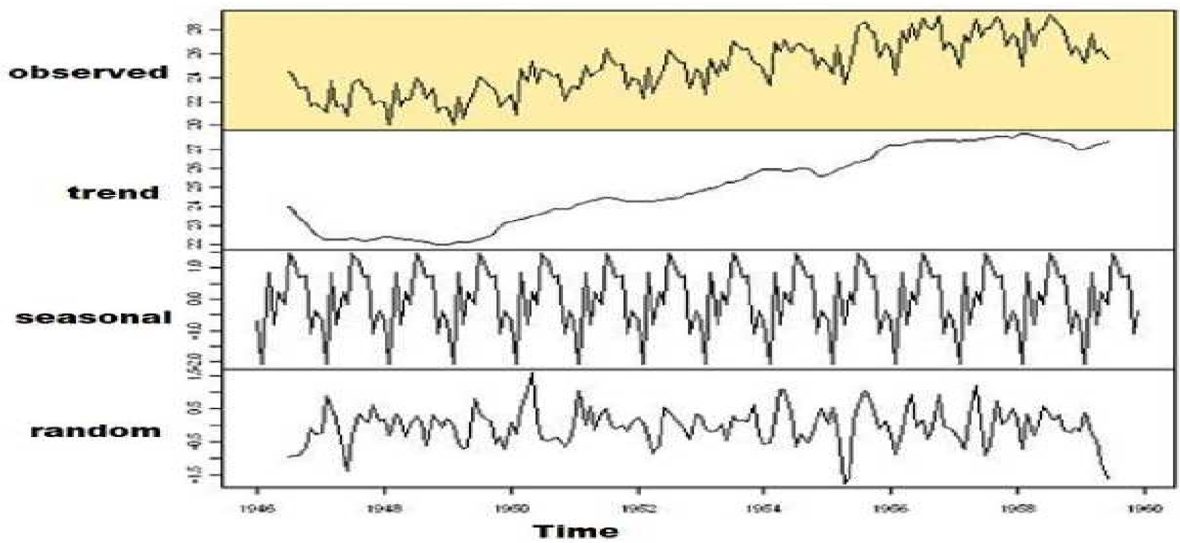


**Figure 2.** Time series

The machine learning algorithm suitable for the purpose of the study is Long Short-Term Memory (LSTM). LSTM is a special type of recurrent neural network that can learn long-term dependencies, i.e. it has recurrent connections. The effect of a given input on the hidden layer, and hence on the output of the network, either decreases or increases exponentially as the network revolves around its recurrent connections. This deficiency is referred to in the literature as the vanishing gradient problem. LSTM is an RNN architecture specifically designed to solve the vanishing gradient problem. LSTM cells consist of gates and weights. An LSTM layer consists of a series of repeatedly interconnected blocks, known as memory blocks. Each contains one or more recurrently connected memory cells and three multiplicative units with input, output and forget gates that provide continuous write, read and reset operations for these cells. The network can interact with cells only through gates [31, 32].

In LSTM modelling, the network is shown one observation from a sequence at a time and can remember which observations it has seen before and how they relate to a prediction. That is, LSTM models can learn and exploit temporal dependence from data. Because of the ability to learn long-term correlations in a sequence, LSTM networks have the ability to accurately model complex multivariate sequences. They can also model multiple parallel input sequences separately [33, 34]. The LSTM model has increased the single neural network in the RNN to 4 and these 4 neural networks are connected to each other in a special $_J$ way. The figure below shows the internal structure of the LSTM model and how these 4 neural networks are connected;

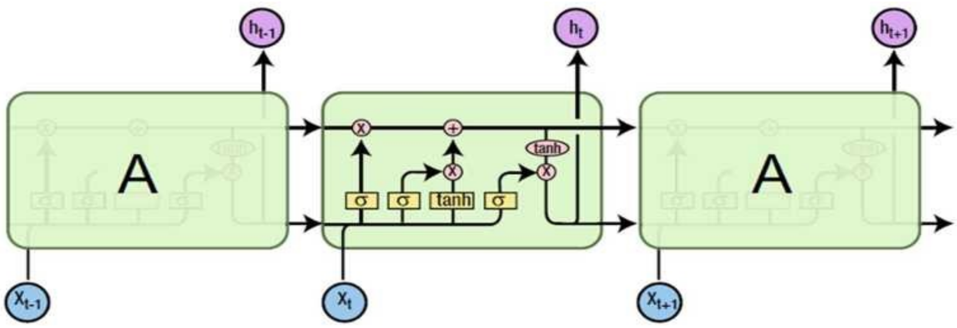


**Figure 3.** Three LSTM cells with four layers

$$
\begin{aligned}
i_t &= \sigma(W_{xi}x_t + W_{hi}h_{t-1} + W_{hc}c_{t-1} + b_i), && (1)\\
f_t &= \sigma(W_{xf}x_t + W_{hf}h_{t-1} + W_{hf}c_{t-1} + b_f), && (2)\\
c_t &= f_t \circ c_{t-1} + i_t \circ \tanh(W_{xc}x_t + W_{hc}h_{t-1} + b_c), && (3)\\
o_t &= \sigma(W_{xo}x_t + W_{ho}h_{t-1} + W_{co}c_t + b_o), && (4)\\
h_t &= o_t \circ \tanh(c_t). && (5)
\end{aligned}
$$

$x_t$ is the input vector, $i_t$ is the input gate in Eq. (1), $f_t$ is the forget gate in Eq. (2), $c_t$ is the cell state in Eq. (3), $o_t$ is the output gate in Eq. (4), $h_t$ is the output vector in Eq. (5), $\sigma$ is the sigmoid activation function and tanh is the tangent hyperbolic activation function [33, 34]. Finally, the definition of a standard sigmoid function $\sigma(x)$ is shown in Eq. (6).

$$\sigma(x) = \frac{1}{1 + e^{-x}}, \tag{6}$$

LSTM is a deep neural network algorithm frequently used in time series forecasting. It was first used in chaotic time series forecasting [35]. LSTM architectures have also been used in speech [36], text processing [37], music [38] and classification [39] applications and successful results have been obtained.

## 2 Background

In recent years, the ability to predict the price movements of dual-listed stocks in financial markets has been recognised as a strategic advantage for international investors. Dual-listed stocks are affected by different market conditions as the same company is traded on different stock exchanges, which creates extra complexity in price-prediction models. While there is extensive literature that machine and deep learning algorithms offer successful results in such complex price forecasts [40–42], the lack of a specific study for dual-listed stocks points to the gap in the literature.

In previous studies, deep learning models (such as LSTM and GRU) and machine learning methods (such as Random Forest and SVM) have succeeded in stock price prediction in various stock markets. For example, it has been reported that high accuracy is achieved in large data sets in predictions made with the LSTM model [43–45] and deep learning provides effective results especially in multivariate time series data [46, 47]. However, Mehtab, Sen, and Dutta (2021) showed that hybrid modelling approaches yielded successful results on more complex market data, indicating the applicability of hybrid models for dual-listed stock forecasting [41]. This research makes a unique contribution to the existing literature by comparing machine and deep learning algorithms for price prediction of dual-listed stocks. The applicability of such a study may enable investors and market analysts to use machine learning and deep learning methods more effectively in their strategic investment decisions. In this context, the current study makes an innovative contribution to investment strategies by providing a new methodological framework for dual-listed stock price forecasting [12, 47, 48].

## 3 Data description

The aim of the study is to predict the prices of Turkcell shares, which are dual-registered in BIST and NYSE, using a machine learning and a deep learning algorithm. Thus, two different artificial intelligence applications are compared and it is determined which prediction method gives more realistic results in different stock exchanges. It is also determined which stock exchange is more predictable.

The dataset used in the study consists of daily closing values of Turkcell's stock prices in BIST and NYSE between January 4, 2010 and December 2, 2023. The data was taken from https://finance.yahoo.com/ using the yfinance library in the Python programming language. For the purpose of creating an example, a total of 10 data from the dataset, the first 5 and the last 5, are shown in Table 1.

**Table 1.** Sample data from the dataset

| Sequence | Date | Price_BIST | Price_NYSE |
|---|---|---|---|
| 1 | 2023-12-29 | 56.10 | 48.10 |
| 2 | 2023-12-28 | 56.20 | 48.10 |
| 3 | 2023-12-27 | 53.70 | 46.90 |
| 4 | 2023-12-26 | 53.10 | 47.00 |
| 5 | 2023-12-22 | 55.05 | 48.40 |
| 3394 | 2010-01-08 | 6.68 | 19.42 |
| 3395 | 2010-01-07 | 6.80 | 19.57 |
| 3396 | 2010-01-06 | 6.68 | 19.13 |
| 3397 | 2010-01-05 | 6.56 | 18.90 |
| 3398 | 2010-01-04 | 6.33 | 18.12 |

Table 2 shows the variables in the data set and their ranges.

**Table 2.** Value range of variables in the data set

| Dataset Variables | Ranges | |
|---|---|---|
| | Lower value | Upper value |
| BIST TCELL closing prices (normalized) | 4.51 | 60.55 |
| NYSE TKC closing prices (normalized) | 2.35 | 19.98 |

The comparative distribution graph of Turkcell stock closing prices for NYSE and BIST, created using the graphic feature in the Matplotlib library, is given in Figure 4.

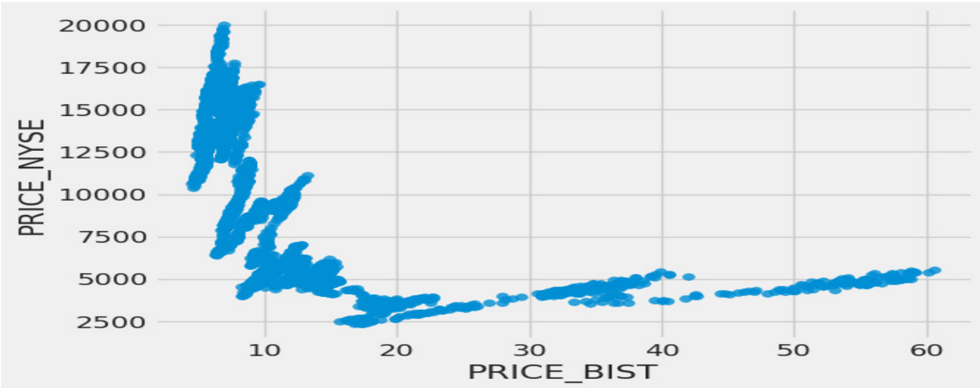


**Figure 4.** Comparative distribution of closing stock prices

## 4 Method

In this study, which was conducted to predict dual-listed stock prices in different stock exchanges, the prediction of which stock exchange is more predictable based on the obtained stock exchange data was examined with Random Forest Regressor (RF) from machine learning algorithms and Long Short-Term Memory (LSTM) from deep learning algorithms. In addition, the comparative results of the two methods (RF and LSTM) were also examined. The reason for preferring these methods is that they produce acceptable results in the literature in processing sequential data such as time series. In the literature, [49] and [50] used RF and LSTM models for financial market predictions in the prediction of time series. Due to complex features such as nonlinearity, nonstationarity and series correlation, financial data pose a great estimation challenge. Fischer and Krauss proved in their research that the LSTM model provides significant results compared to more traditional prediction models such as Random Forest, Standard Deep Neural Network and Standard Logistic Regression [49–51].

The reasons for the preference of the methods can be expressed in more detail in the form of a model comparison with the justifications as follows; LSTM (Long Short-Term Memory) models are frequently preferred in financial forecasting due to their capacity to learn sequential dependencies in time series data. The ability to understand patterns in time series data based on past data and to effectively capture long-run dependencies provides an advantage, especially in complex data such as stock prices. Various studies in the literature have supported this aspect of LSTM. For example, Fischer and Krauss (2018) compared the prediction accuracy of LSTM in the financial market with other methods and stated that this model performs better thanks to its ability to learn from past data [50]. Bao et al. (2017) stated that LSTM provides more accurate forecasts by effectively capturing non-linear and sequential dependencies in the stock market [52]. Zhong and Enke (2017) further demonstrated that LSTM's ability to model sequential patterns in stock price movements makes it superior to traditional methods like Support Vector Machines, particularly in complex market environments [53].

The unique architecture of LSTM, introduced by Hochreiter and Schmidhuber (1997), enables the model to address the vanishing gradient problem commonly encountered in traditional recurrent neural networks (RNNs) [54]. This feature allows LSTM to retain relevant information over long sequences, making it particularly effective for financial time series data where long-term dependencies play a critical role. Additionally, its gating mechanisms help the model selectively filter important information while discarding irrelevant data, enhancing its performance in noisy datasets [55].

RF, on the other hand, generally stands out with its performance in modelling non-linear relationships and data with high variability. Patel et al. (2015) highlighted how RF's ensemble learning structure effectively captures non-linear relationships and reduces overfitting in highly volatile financial markets [56]. These advantages of RF are supported by the work of Breiman (2001), who emphasised the ability of RF to model non-linear relationships [57].

While LSTM's advanced architecture offers superior prediction performance in complex datasets, its complexity poses challenges for interpretability and practical application. Conversely, RF provides a more accessible and interpretable framework, making it suitable for practitioners who prioritize simplicity and usability over absolute predictive performance. As demonstrated by Singh and Gupta (2020), model choice should balance predictive power with interpretability, particularly in scenarios where explainability is critical for decision-making [58].

In time series forecasting, both Random Forest (RF) and Long Short-Term Memory (LSTM) models are frequently used to predict future values based on past observations. These models aim to map the current time step, denoted as $t$, to the following time step, $(t+1)$, by learning the temporal dependencies present in the data. The Random Forest model is a tree-based ensemble method that utilizes lagged features-past observations at time $t$-as input predictors to estimate the target value for $(t+1)$. RF effectively captures non-linear relationships and assesses feature importance; however, it does not inherently model sequential patterns over time. In contrast, the LSTM is a specialized recurrent neural network (RNN) designed to handle long-term dependencies and sequential data through its memory cell structure, which retains information across multiple time steps. By training on sliding windows of sequential data, the LSTM learns the temporal patterns and forecasts $(t+1)$ values based on the historical input at time $t$. Both approaches operate within a supervised learning framework, where past observations serve as input and future values serve as targets. This enables the models to generalize and predict the next time step in the series.

The steps taken in the Random Forest (RF) model were explained. Following this, the steps for the Long Short-Term Memory (LSTM) model were described. It should be noted that the first three steps were the same for both the RF and LSTM models given as follows.

- Step 1- Reading and editing the data: The data in the finance.yahoo.com database was read with the help of the yfinance library and edited with the Pandas library. In the editing phase, the closing prices and date data to be used in the data set were pulled as a time series.
- Step 2- Preprocessing of data: Closing price data is normalized between 0 and 1. For this, the MinMaxScaler class from the Preprocessing module of the SciKit-Learn library is used. The formula used in the calculation is given in Eq. (7), and the first 5 and last 5 of the normalized data are shown in Table 3 as an example.

$$X_{scaled} = \frac{X - X_{min}}{X_{max} - X_{min}}. \tag{7}$$

**Table 3.** Sample data from the normalized dataset

| Sequence | Data | NormPrice_BIST | NormPrice_NYSE |
|---|---|---|---|
| 1 | 2023-12-29 | 0.920592 | 0.139535 |
| 2 | 2023-12-28 | 0.922377 | 0.139535 |
| 3 | 2023-12-27 | 0.877766 | 0.132728 |
| 4 | 2023-12-26 | 0.867059 | 0.133296 |
| 5 | 2023-12-22 | 0.901856 | 0.141237 |
| 3394 | 2010-01-08 | 0.038722 | 0.968236 |
| 3395 | 2010-01-07 | 0.040864 | 0.976744 |
| 3396 | 2010-01-06 | 0.038722 | 0.951787 |
| 3397 | 2010-01-05 | 0.036581 | 0.938741 |
| 3398 | 2010-01-04 | 0.032477 | 0.894498 |

- Step 3- Creating training and test data sets: In the data set taken as source data, daily stock closing prices for the time period from 04.01.2010 to 29.12.2023 were used as the training (train set) set. The part from 02.01.2024 to 31.05.2024 was used as the test set to measure the performance of the model. X train represents the $t$ moment, and Y train represents the $t+1$ moment.

Utilizing the current time point $(t)$ to predict the subsequent time point $(t+1)$ is a widely accepted approach in the analysis of time-dependent data, given its sequential and autoregressive characteristics. The underlying premise is that the present state $(t)$ encapsulates sufficient information regarding the dynamics of the system, enabling accurate forecasting of the immediate future $(t+1)$. This methodology is consistent with the Markov property, which posits that the future state is primarily dependent on the current state. Consequently, this reduces the complexity of the predictive model while preserving its accuracy. The practice of selecting a lag of 1 (i.e., employing $t$ to predict $t+1$) is prevalent, as numerous time series processes exhibit robust autocorrelation between successive observations. A lag of 1 effectively captures the most immediate and significant dependencies, which frequently dominate in various practical contexts such as financial forecasting, meteorological predictions, and system monitoring. Nevertheless, the appropriate choice of lag may vary according to the specific domain and the temporal characteristics inherent to the data. For instance, longer lags may be necessary in cases involving seasonal data or delayed effects between variables. This methodological framework is substantiated by empirical research. Notably, Box and Jenkins (1970) pioneered the Autoregressive Integrated Moving Average (ARIMA) model, which incorporates lagged values to elucidate the dependency structure of time series data [59].

Random Forest regression estimation was performed using the Pandas, Numpy, and SciKit-Learn libraries, with the assistance of Google Cloud service Colab. The subsequent steps are as follows:

- Step 4- Creating the prediction model with the Random Forest Regressor algorithm: The Random Forest Regressor class from the Ensemble models of the SciKit-Learn library was used. The decision tree parameter of this algorithm was taken as 100, and the random state was taken as 42. The prediction model was obtained by training the algorithm with the training set created in Step 4.
- Step 5- Making the estimation and measuring its accuracy: The model obtained in Step 4 was given the test data in Step 3 and estimations were produced. The obtained estimations were compared with the realized end-of-day closing prices and the performance of the model was reported. The actual values and the estimation values were presented in graphs with the help of the Matplotlib library.

These steps were repeated separately for both exchanges.
For the LSTM prediction method, the first three steps given in RF are applied as is. Creating the prediction model with LSTM is explained below starting from Step 4.

- Step 1- Reading and editing the data,
- Step 2- Preprocessing of the given,
- Step 3- Creating training and test data sets,
- Step 4- Creation and visualization of the LSTM algorithm: In order to create the deep learning structure, the Sequential class and Dense layer types were added to the model types from the Keras Library since the data is time series. The first LSTM layer is configured with 50 neurons and the parameter 'return_sequences=True', which means that it will return an output for each time step. The second LSTM layer is also configured with 50 neurons and the parameter 'return_sequences=False'. This means that it will return an output only for the last time step. The last Dense layer, which contains 25 neurons and is used as the output layer, contains a single neuron and produces the value predicted by the model. Figure 5 is given to visualize the architecture of the LSTM model. This architecture includes the LSTM and Dense layers used to process the time series data. The figure indicates each layer and the connections between the layers.

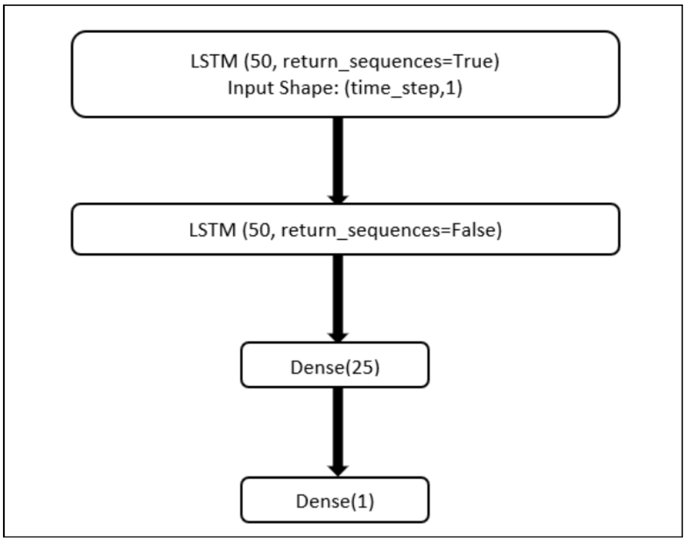


**Figure 5.** LSTM model architecture

- Step 5- Performing the estimation process and measuring its accuracy: Training and test data were estimated with the variable assigned to the Sequential class. The Adam optimization algorithm was used to optimize the model. Adam is an optimization algorithm with an adaptive learning rate and has a wide range of applications. Mean Squared Error (MSE) was used as the loss function. After the estimation processes, the data were normalized and returned to their normal structures, and the observation values, training estimation values, and test estimation values were shown in the graph with the help of the Matplotlib library.

These steps were repeated separately for both stock exchanges.

## 5 Analysis and findings

As a result of the above steps, mean squared error (MSE) values were calculated in order to measure the performance of the machine and deep learning models that have completed their training. The MSE error value, MAPE, and sMAPE are calculated as shown in Eqs. (8), (9), and (10), respectively [58], which are given in Table 4. MSE is calculated by taking the average of the square of the difference between the values predicted by the model and the actual values, which is widely used in regression problems.

$$MSE = \frac{1}{n}\sum_{i=1}^{n} e_i^2, \tag{8}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} \frac{|A_i - F_i|}{A_i}, \tag{9}$$

$A_i$ is the actual value,

$F_i$ is the forecast value,

$n$ is the actual value,

$$SMAPE = \frac{1}{n}\sum_{i=1}^{n} \frac{|A_i - F_i|}{(|A_i| + |F_i|)/2}. \tag{10}$$

**Table 4.** MSE, MAPE and sMAPE values of machine and deep learning methods on the test sets

| | Algorithms | Variables | MSE | MAPE | sMAPE |
|---|---|---|---|---|---|
| | RF | BIST TCELL | 2.36498 | 1,70129 | 1,694788 |
| Test Set | | NYSE TKC | 0.01163 | 1,43202 | 1,42751 |
| | LSTM | BIST TCELL | 2.16346 | 1,59135 | 1,583288 |
| | | NYSE TKC | 0.01668 | 1,797863 | 1,77944 |
| | RF | BIST TCELL | 0.049372 | 0.203967 | 0.203952 |
| Train Set | | NYSE TKC | 0.000670 | 0.301825 | 0.301779 |
| | LSTM | BIST TCELL | 1.290119 | 1.034096 | 1.026132 |
| | | NYSE TKC | 0.00121 | 0.399714 | 0.398960 |

When the metric error values of the machine learning algorithm are examined, it is determined that the error value of the RF Regression model is 2.36498 for BIST and 0.01163 for NYSE. The error value results of the deep learning algorithms are determined as 2.16346 for BIST and 0.01668 for NYSE.

In the BIST TCELL dataset, LSTM demonstrates superior performance by achieving lower MAPE (1.59135 vs. 1.70129) and sMAPE (1.583288 vs. 1.694788) values. In the NYSE TKC dataset, RF exhibits superior performance, reflected in lower MAPE (1.43202 vs. 1.797863) and sMAPE (1.42751 vs. 1.77944) values. Moreover, the consistent alignment between MAPE and sMAPE across both datasets affirms the reliability of these metrics as evaluative tools for predictive accuracy. Figure 6 and Figure 7 visualize the graphical representation of the actual closing prices and estimated values of the data for the RF and LSTM algorithms used to predict Turkcell stock prices in Borsa Istanbul.

These steps were repeated separately for both exchanges.

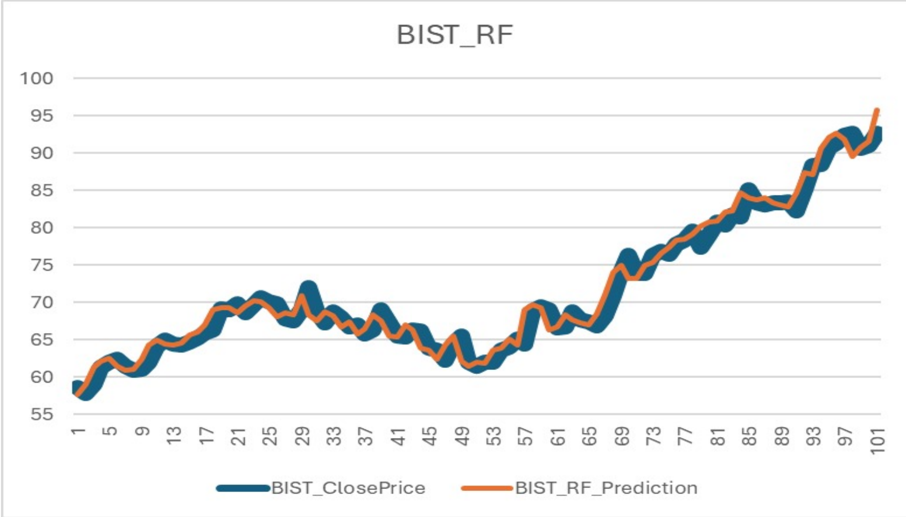


**Figure 6.** BIST TCELL stock price prediction graph of RF algorithm

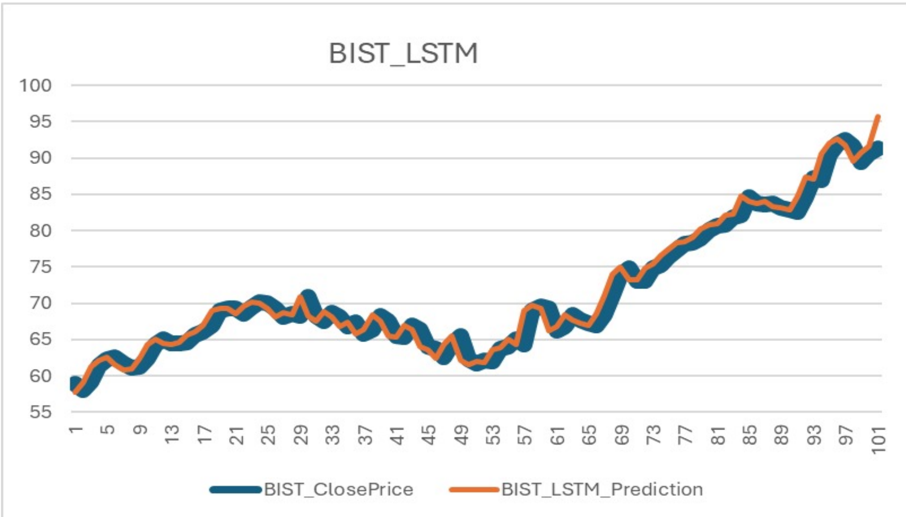


**Figure 7.** BIST TCELL stock price prediction graph of LSTM algorithm

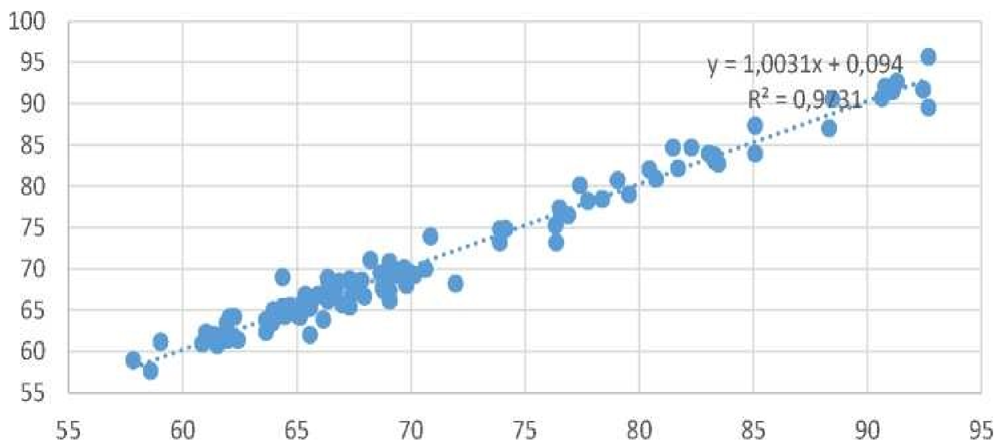


**Figure 8.** BIST TCELL stock price prediction model with RF algorithm

In the BIST TCELL stock price prediction graphs seen in Figure 6 and Figure 7, the part drawn in blue shows the real closing prices of the stock, while the part drawn in orange shows the estimated prices obtained with the help of RF and LSTM algorithms. In Figure 8 and Figure 9, the $R^2$ values with RF and LSTM regression models are seen, respectively. Accordingly, it is seen that the $R^2$ value in the RF algorithm for BIST TCELL stock price prediction is 0.9731 and 0.9769 for the LSTM algorithm. Therefore, it is stated that the regression prediction model fit established for both algorithms is good.

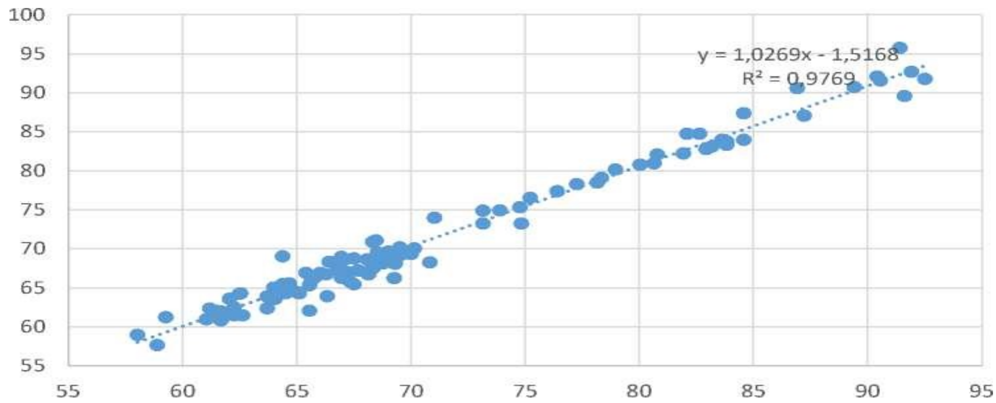


**Figure 9.** BIST TCELL stock price prediction model with LSTM algorithm

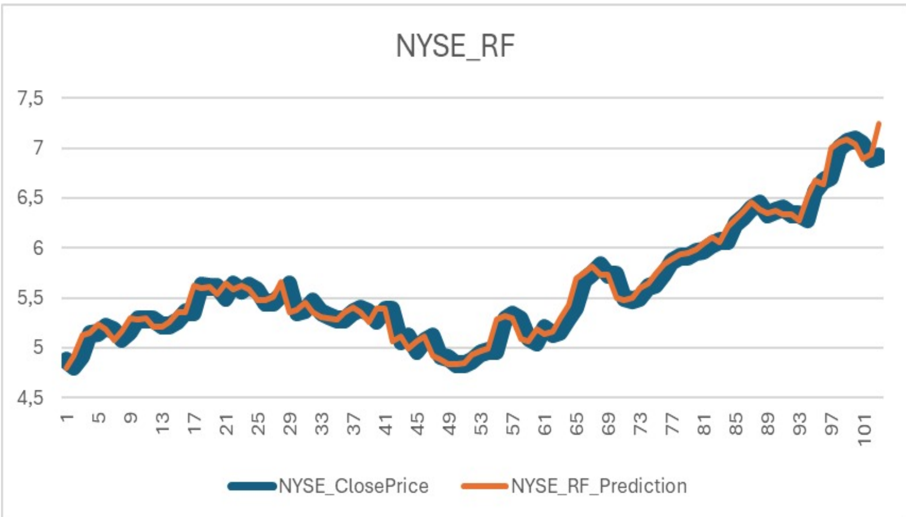


**Figure 10.** NYSE TKC stock price prediction chart of RF algorithm

The graphical representation of the actual closing prices and estimated values of the data for the RF and LSTM algorithms used to estimate the prices of Turkcell (TKC) traded on the NYSE is visualized in Figure 10 and Figure 11. In the NYSE TKC stock price prediction graphs seen in Figure 10 and Figure 11, the part drawn in blue shows the real closing prices of the stock, while the part drawn in orange shows the estimated prices obtained with the help of RF and LSTM algorithms. In Figure 12 and Figure 13 below, the $R^2$ values with RF and LSTM regression models are seen, respectively. Accordingly, it is seen that the $R^2$ value in the RF algorithm for NYSE TKC stock price prediction is 0.9653 and 0.9642 for the LSTM algorithm. Therefore, it is stated that the regression prediction model fit established for both algorithms is good.

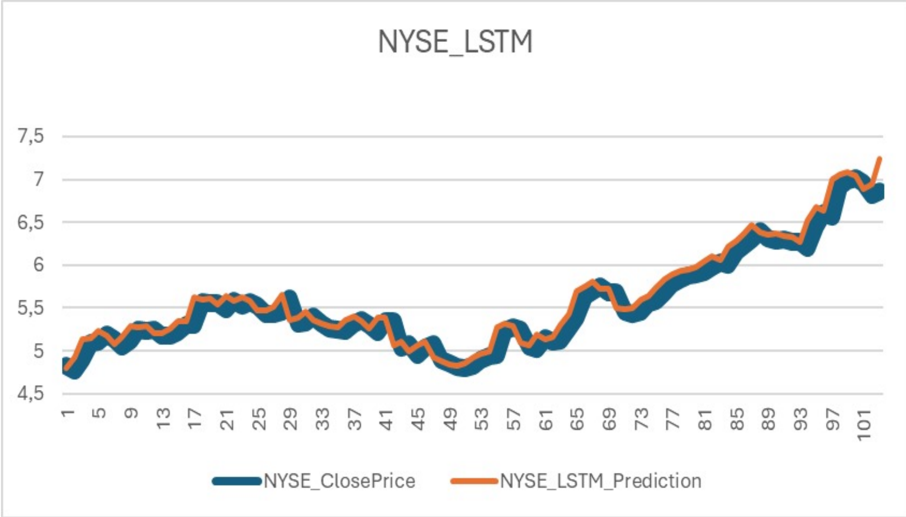


**Figure 11.** NYSE TKC stock price prediction graph of LSTM algorithm

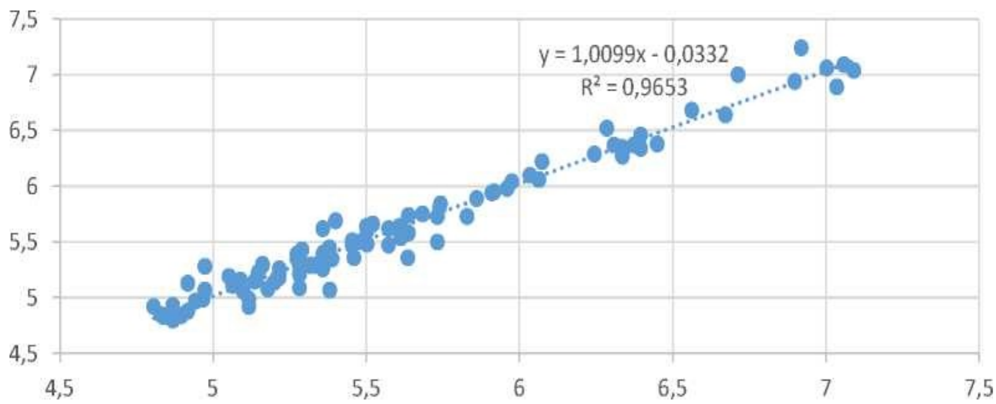


**Figure 12.** NYSE TKC stock price prediction model with RF algorithm

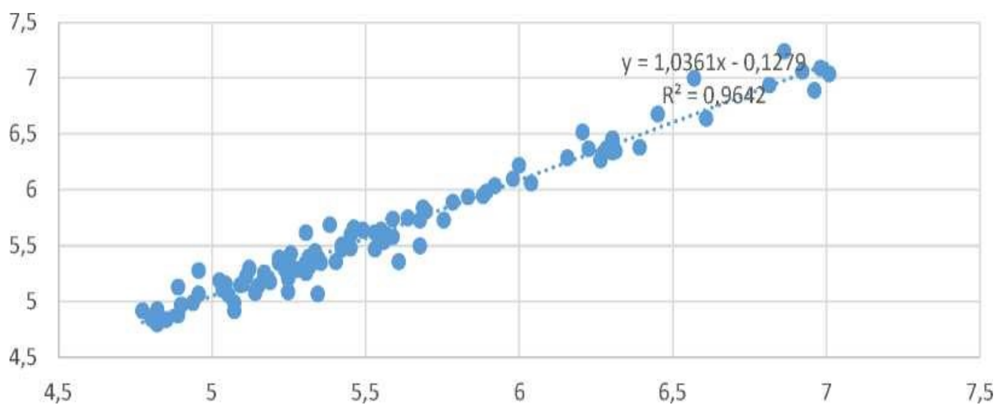


**Figure 13.** NYSE TKC stock price prediction model with LSTM algorithm

In time series forecasting, traditional cross-validation methods are not applicable due to the inherent temporal dependencies present within the data. Unlike standard k-fold cross-validation, which permits random shuffling of data, time series data necessitates the maintenance of chronological order to prevent data leakage and ensure realistic model evaluation. To address this issue, the TimeSeriesSplit method was employed in this study. This method facilitates the sequential partitioning of data into training and test sets while preserving temporal continuity. The training set is incrementally expanded, and the test set is shifted forward, thereby simulating real-world forecasting scenarios. Through the application of TimeSeriesSplit, overfitting was evaluated across multiple splits, thereby ensuring that the model's performance was assessed using unseen, future-like data. This methodology offers a robust validation framework for time series analysis. The split number was established based on the dataset size, which comprises approximately 3,650 data points in the train set, and 180 data points in the test set. The optimal split number was calculated to be approximately 20 using the Eq. (11). This selection is intended to ensure adequate test data coverage and reliable validation of the model.

$$\text{Number of Splits}=(\text{Total Data Size-Test Size})/\text{Test Size}. \tag{11}$$

This approach ensures that each fold contains a sufficient amount of training data while adhering to the temporal structure of the dataset, a critical requirement for time series analysis. Although the formula itself is not explicitly formalized in the literature, it aligns with established principles of time series cross-validation, as discussed in works such as Hyndman and Athanasopoulos (2018) and Bergmeir et al. (2018). These studies emphasize the importance of preserving temporal order and preventing data leakage when evaluating predictive models, thereby supporting the rationale for such a split design [60, 61].
The average of the results obtained for each split according to the metrics is given in Table 5.

**Table 5.** Performance comparison of RF and LSTM models using TimeSeriesSplit cross-validation on Train and Test Datasets

| | | MSE_Test | MAPE_Test | sMAPE_Test | MSE_Train | MAPE_Train | sMAPE_Train |
|---|---|---|---|---|---|---|---|
| RF | BIST | 0.079301 | 0.000922 | 0.093044 | 0.000011 | 0.000011 | 0.001080 |
| | NYSE | 0.003465 | 0.003435 | 0.338088 | 0.000001 | 0.000044 | 0.004376 |
| LSTM | BIST | 1.919818 | 0.019057 | 1.927242 | 0.910750 | 0.012922 | 1.292173 |
| | NYSE | 0.872288 | 0.127579 | 3.311215 | 0.833910 | 0.094173 | 2.571887 |

Table 5 provides a detailed comparison of the Mean Squared Error (MSE), Mean Absolute Percentage Error (MAPE), and Symmetric Mean Absolute Percentage Error (sMAPE) for both training and test sets across two datasets: BIST and NYSE. The Random Forest (RF) model illustrates a robust generalization capability, characterized by minimal discrepancies between training and test errors across all evaluated metrics (MSE, MAPE, and sMAPE). In a similar vein, the Long Short-Term Memory (LSTM) model demonstrates competent generalization, although it exhibits slightly elevated sMAPE values within the NYSE dataset. Collectively, these findings affirm that both models effectively generalize to unseen data, as the error metrics for the training and test sets remain consistently aligned throughout the 20-fold validation process.

## 6 Results and discussion

In the context of mathematical modelling, RF (credit scoring in finance, disease diagnosis in healthcare and customer segmentation in marketing) and LSTM (chaotic time series prediction, speech analysis, text processing analysis, music processing analysis and classification) algorithms have a broad range of applications and modelling areas for big data. In this study, we employ both random forest (RF) and long short-term memory (LSTM) algorithms to model the New York Stock Exchange (NYSE) and the Frankfurt Stock Exchange (BSE), or FSE, as it is also known. We then perform a comparative analysis of dual-listed stocks.

The objective of this study is to predict the closing prices of Turkcell stocks, which are traded in two different organised markets, using a random forest (RF) algorithm, which is a machine learning method, and a long short-term memory (LSTM) algorithm, which is a deep learning method. The aim is also to determine which stock market is better predicted by which algorithm. The algorithms were constructed with the assistance of Colab, a Google cloud service. In the study, the data in the finance.yahoo.com database were retrieved with the assistance of the yfinance library and organised with the Pandas library. The efficacy of the predictive outcomes was evaluated through the utilisation of mean square error (MSE) error metrics.

The efficacy of machine learning and deep learning algorithms in forecasting the closing values of Turkcell stock prices on BIST and NYSE is assessed on a stock exchange-by-stock exchange basis. In consequence, the root-mean-square error (RMSE) values for RF, one of the machine learning models, were determined to be 2.36498 for BIST and 0.01163 for NYSE. The results demonstrate that the RF algorithm exhibits a lower error rate in predicting the closing prices of Turkcell stocks on the NYSE. It can therefore be concluded that the NYSE is a more predictable stock market for the RF algorithm.

The mean squared error (MSE) values for the long short-term memory (LSTM) model, one of the deep learning models, are 2.16346 for the BIST and 0.01668 for the NYSE. The results demonstrate that the LSTM algorithm exhibits a lower error rate in predicting the closing prices of Turkcell stocks on the NYSE stock exchange. It can therefore be concluded that the NYSE is a more predictable stock market for the LSTM algorithm than for the RF algorithm.

In this study, it is found that LSTM outperforms RF in predicting dual-listed stock prices on both NYSE and BIST. This is due to the special design of LSTM for sequential data processing. LSTM uses cell states and gate mechanisms to model long-term dependencies in time series data [54]. These mechanisms enable LSTM to capture temporal dependencies and complex non-linear patterns. Stock price data often contain time series that exhibit high volatility and memory dependencies. Therefore, LSTM's ability to learn long-term relationships makes it possible to achieve a higher prediction accuracy on such data. However, although RF can model non-linear relationships well, it is limited in understanding sequential patterns or long-term dependencies between time series. The basic structure of RF is based on independent and unordered variables, which makes it difficult to explicitly model temporal relationships in time series data [57].

Stock prices are often characterised as complex time series that exhibit non-linear dynamics and memory dependencies. For example, the influence of market trends, macroeconomic indicators, and news flows can cause prices to exhibit sequential dependence [53]. Such complex structures make the limitations of RF more apparent, while emphasising the superiority of LSTM in sequential data. Bao, Yue, and Rao (2017) examined the performance of LSTM on sequential and non-linear data structures and showed that LSTM processes such data structures more effectively than RF [52].

The advantages of LSTM in time series data have been widely documented in the literature. Fischer and Krauss (2018) demonstrate the superior performance of LSTM in price forecasting in financial markets, while emphasising the limitations of traditional methods such as RF in capturing sequential dependencies [50]. Furthermore, Siami-Namini et al. (2019) argue that LSTM has the potential to improve accuracy in financial time series data, while RF lags behind in this regard. However, the limitations of RF regarding sequential patterns have also been addressed in the literature [62]. For example, Biau and Scornet (2016) attribute the limited performance of RF on sequential time series data to the model's dependence on independent variables. These limitations provide an important context explaining why LSTM performs better on complex financial time series data [63].

The possible reasons for the findings of the study can be listed as follows:

- NYSE is purported to possess the highest liquidity in the US stock markets, thereby conferring substantial benefits in terms of price discovery and market stability [64].
- NYSE has a proven track record of outperforming during periods of market volatility. To illustrate, an examination of an especially volatile market period in 2022 reveals that NYSE-listed companies exhibited tighter quoted spreads and achieved superior accuracy in the opening and closing auctions [64].
- The BIST stock exchange is characterised by high volatility.
- In comparison to the NYSE, the BIST has experienced a greater number of periods of market disruption, including the Gezi events, the global pandemic of 2020, and the 6 February earthquakes.

Moreover, in terms of algorithms, RF has a lower error rate than LSTM. This result is similar to the results of [65] and [66] in the literature.

There are several advantages of using the findings of this study by policy makers, potential researchers, investors and financial analysts. If the results are evaluated from the perspective of each user, the following comments can be obtained for policy makers:

- The fact that NYSE is more predictable than BIST suggests that market transparency and data quality may be higher at NYSE. Therefore, steps can be taken to increase market transparency on BIST and to develop mechanisms that provide higher quality data.
- Given the effectiveness of machine learning and deep learning methods in stock market predictions, market regulators and exchange operators in Turkey could develop the necessary infrastructure to increase the use of such technologies.
- Universities and research institutions could develop funding and scholarship programs to support studies on financial forecasting models.
- NYSE's high predictability indicates its proximity to international market standards. In this context, harmonizing BIST's trading systems, regulations and technological infrastructure with international standards may increase the confidence of market participants.
- Investors should be more informed about the predictability and volatility structure of stock markets. Therefore, investor education programs on BIST should be increased and tools should be developed to help them better understand market movements.
- Implementation of policy instruments that reduce market volatility may allow for better financial forecasts.
- Develop a flexible regulatory framework that can keep pace with the pace of technological developments while maintaining market stability. This could provide a more reliable environment for both local and international investors.

The following suggestions can be listed for potential researchers and future studies:

- The current study only focuses on a specific set of stock prices. Future studies can test whether the results can be generalized by conducting similar analyses on dual-listed stocks in different sectors.
- Apart from the algorithms used in the study, the prediction performance of other machine and deep learning algorithms can be examined.
- The differences in the predictability of NYSE and BIST may be due to market dynamics and macroeconomic factors. In future studies, the impact of macroeconomic variables such as interest rates, exchange rates, and inflation rates can be included in the model.
- The performance of hybrid approaches can be examined by combining machine learning and deep learning models instead of one algorithm each.

- Future research could compare the prediction performance of the models under different market conditions (bull or bear market).
- In this study, only the MSE measure is considered. In future studies, additional measures such as MAPE, sMAPE can be used to evaluate the performance more comprehensively.
- Apart from the comparison between NYSE and BIST, the predictability of dual-listed stocks on other international exchanges can be investigated. Such studies may help to better understand the impact of different market characteristics on forecasting performance.

Various recommendations for investors can be listed as follows:

- The findings suggest that NYSE is more predictable than BIST. Therefore, investors can make more accurate investment decisions and optimize their risks by using forecasting models for stocks traded on NYSE.
- Investors should prioritize not only intuitive approaches but also data-driven methods in their decision-making processes. They can assess the accuracy of forecasting models by taking into account error measures such as MSE while shaping their investment strategies.
- The fact that NYSE is more predictable can be interpreted as investors can optimize their investments by choosing this stock exchange in their portfolio diversification strategy.
- The fact that BIST has higher error rates may require a more careful and comprehensive analysis. Investors may adopt a more conservative approach and use additional data when trading in this market.
- Investors should familiarize themselves with machine learning and deep learning technologies to understand their potential and learn how to integrate them into their strategies. To this end, they can invest in relevant software, analysis tools and training programs.

The recommendations for financial analysts are as follows:

- Analysts can develop strategies specific to different markets, taking into account stock market characteristics when using forecasting models.
- Although the NYSE is more predictable, macroeconomic and regional influences in the markets should be taken into account. By incorporating such factors into the forecasting process, analysts can make more comprehensive assessments and minimize error rates.
- Where the NYSE is more predictable, analysts can provide risk and return analysis based on more accurate forecasts.
- Analysts can improve the accuracy of their forecasting models by relying not only on historical price data, but also on additional data sources such as news feeds, social media sentiment, and economic indicators.
- Models vary in their error rates. Analysts can develop a deeper understanding of market structure by examining the reasons for these errors in detail.
- Analysts can go beyond the comparison of NYSE and BIST to perform similar model analyses on other international stock exchanges and make generalizations about market predictability.

All of the suggestions listed can contribute to making financial markets more efficient and predictable. It can also be stated that investors will increase their financial success by making more informed and data-driven decisions. In addition, it may enable financial analysts to make more accurate forecasts and develop strategies that support investment decisions.

The absence of any previous study in which dual-listed stocks are predicted by machine and deep learning algorithms indicates that this study makes a valuable contribution to the existing literature. It may be recommended that future studies conduct periodic analyses and examine stocks registered in other stock exchanges. In this study, a cross-sectional time series of stock markets was subjected to analysis. In future studies, it would be beneficial to create price forecasts and stock market forecasting models for stocks registered in two different stock exchanges, utilising large data sets. The success rates of these forecasts and the forecasting times of those that prove successful can be subjected to analysis.

## Declarations

### Use of AI tools

The authors declare that they have not used Artificial Intelligence (AI) tools in the creation of this article.

### Data availability statement

No Data associated with the manuscript.

### Ethical approval (optional)

The authors state that this research complies with ethical standards. This research does not involve either human participants or animals.

### Consent for publication

Not applicable

### Conflicts of interest

The authors declare that they have no conflict of interest.

### Funding

No funding was received for this research.

### Author's contributions

E.N.C.K.: Conceptualization, Writing - Original Draft, Writing - Review & Editing, Supervision. G.Ş.: Conceptualization, Data Curation, Writing - Original Draft, Supervision, Methodology. E.K.: Conceptualization, Writing - Original Draft. K.K.: Conceptualization, Writing - Original Draft, Writing - Review & Editing, Methodology, Supervision, Methodology. A.M.A.: Formal Analysis, Visualization. All authors discussed the results and contributed to the final manuscript.

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