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Predicting Stock Prices Using Machine Learning Methods and Deep Learning Algorithms: The Sample of the Istanbul Stock Exchange

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Highlights

- The paper focusessed on Istanbul Stock Exchange (ISE) prediction
- MLP, SVM and LSTM models were compared with their forecasting performances
- MLP and LSTM models outperformed SVM model in estimating the stock prices

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Abstract

Stock market prediction in financial and commodity markets is a major challenge for speculators, investors, and companies but also profitable with an accurate prediction. Thus, obtaining accurate prediction results becomes extremely important especially while the stock market is essentially volatile, nonlinear, complicated, adaptive, nonparametric and unpredictable in nature. This study aims to forecast the opening and closing stock prices of 42 firms listed in Istanbul Stock Exchange National 100 Index (ISE-100) using well-known machine learning methods, Multilayer Perceptrons (MLP) and Support Vector Machines (SVM) models and deep learning algorithm, Long Short Term Memory (LSTM) by comparing their forecasting performances. The analysis includes 9 years of data from 01.01.2010 to 01.01.2019. For each firm 2249 data for the opening and 2249 for the closing stock prices were established as daily data sets. Forecasting performance of these methods was evaluated by applying different criteria for each model: root mean squared error (RMSE), mean squared error (MSE) and R-squared (R2). The results of this study show that MLP and LSTM models become advantageous in estimating the opening and closing stock prices comparing to SVM model.

1. INTRODUCTION

Stock market prediction in financial and commodity markets is a major challenge facing speculators, investors, and companies assuming that future events are at least partly dependent on current and past events and data in their search for market forecasting. However, financial time series are among the noisiest and most difficult signals to predict since the stock market is essentially volatile, nonlinear, complicated, adaptive, nonparametric and unpredictable in nature [1-3]. In finance, many macro-economic issues such as firm policies, political events, general economic circumstances and expectations of traders affect the stock market's movements [3-5]. It is therefore quite difficult to predict changes in financial market prices. According to academic research, market price movements are not random. Instead, they act in a highly non-linear, dynamic way [2], [6]. However, in recent years, the development of computer hardware and software technologies has made it possible to support computation in finance. Thanks to its potential to generate great profits and capital, this use of artificial intelligence resources in the finance industry is of great interest. Therefore, an emerging discipline, computational finance which is the integration of economics, mathematics, and large-scale computation has gained considerable interest and motivated further researches in multi-disciplines [4-5].

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Machine learning methods widely used in the stock forecasting model are support vector machines (SVM), neural networks (NN), models combining them with other algorithms and Long Short-term Memory (LSTM) as a deep learning method. There have been a number of studies using artificial neural networks (ANNs) in time-series modeling and forecasting [7] and ANN models have been used successfully in forecasting studies across a wide range of disciplines. We will begin by presenting the most well-known and widely-used network, multi-layer feedforward networks, which is a particular structure of ANNs applied in a variety of applications including forecasting. One of the first successful applications of multilayer perceptron (MLP) was reported by [8] and following years many other problems have been solved by MLP including student grade point averages [9], ozone level [10], commodity prices [11], advertising [12], electric load consumption [13], forecasting macroeconomic data [14], railway traffic forecasting [15] and financial time series forecasting [16]. Forecasting financial markets such as the stock markets have been researched at length in [17]'s study. The same year, the Standard & Poors 500 Index has been modeled by [18] using different neural network architectures that can be trained to perform, yet the probabilistic neural network performs slightly better than the multilayer perceptron. Mostafa [19] used multi-layer perceptron (MLP) and generalized regression neural networks in order to forecast the Kuwait Stock Exchange (KSE) closing price changes using data for the period 2001-2003 which has concluded that neural networks are performing well in predicting stock exchange movements in developing markets. In their papers, Naeini et al. [20] have used two forms of neural networks, a feedforward Multilayer Perceptron (MLP) and an Elman recurrent network to estimate a company's stock value based on its market-value background. The experimental results show that the MLP neural network outperforms Elman recurrent network and linear regression method. Despite the volatility in the markets, multilayer networks with dynamic backpropagation have been used successfully by [21] to predict the stock price of Bombay Stock Exchange (BSE). In Turkey, Kutlu et al. [22] have used Multi-Layer Perceptron and Generalized Feed Forward networks which have better performances than moving averages to predict the Istanbul Stock Exchange (ISE) market index value including the data gathered for the period of July 1, 2001, through February 28, 2003, from the Central Bank of the Republic of Turkey. Yumlu et al. [23] have made a comparison of the multilayer perceptron (MLP), recurrent neural network (RNN) and the mixture of experts (MoE) structure including 12 years data of Istanbul stock exchange (ISE) index (XU100) between the years of 1990 to 2002. Each model has been compared with well-known market-return index criterions including correlation (ξ), mean absolute error (MAE), mean squared error (MSE), hit rate (H_R), positive hit rate (H_R^+) and negative hit rate (H_R^-). Finally, it has been observed that the MoE neural structure is superior over other models. Guresen et al. [24] have assessed the feasibility of neural network models in stock-market predictions including the analyses of dynamic artificial neural network (DAN2), multi-layer perceptron (MLP), and the hybrid neural networks using generalized autoregressive conditional heteroscedasticity (GARCH) to extract new input variables. Each model is compared by Mean Absolute Deviate (MAD) and Mean Square Error (MSE) using actual exchange rate values of the NASDAQ Stock Exchange index on a daily basis.

Although the neural network has been widely used in the field of financial time series forecasting owing to its outstanding learning ability and broad applicability to a variety of business problems, recently the support vector machines (SVM), has been conducted successfully in the prediction of the stock price index movements. [25-28] have demonstrated that support vector machines (SVM), a novel neural network algorithm developed by Vapnik and his colleagues [29], has performed well in classification tasks, regression and time series prediction, respectively. Cao and Tay [30], Tay and Cao [31] recently have questioned whether the SVM is feasible to predict financial time series by comparing it with a multi-layer back-propagation (BP) neural network. For data sets, they used five real futures obtained from the Chicago Mercantile Market and several foreign bond indices. The experiment result shows that SVMs outperform the multi-layer back-propagation (BP) networks where mean absolute error, normalized mean square error, directional symmetry, and weighted directional symmetry has been conducted. By integrating SVR and self-organizing map (SOM), Tay and Cao [32] have introduced a two-stage architecture in order to properly identify the dynamic input-output relationships implicit in the financial data. The parameters such as C and ε used for the kernel functions are basically determined experimentally and it is shown that the overall approach has better prediction performance and higher convergence rate as in contrast to a single SVR approach. Tay and Cao [33] have suggested a modern version of SVR called *C*-ascending SVMs for the prediction of financial series as similar to the discounted least-squares approach whereby the most recent ε-insensitive errors are weighted and the more distant ones are deweighted. A variety of share indexes, including the S&P 500, have been evaluated for both exponential and linear weight functions and it has been concluded that, compared to a standard SVR method, this approach can present better performance. For the purpose of predicting the direction of the change in daily stock price in the Korea composite stock price index (KOS-PI), Kim [34] has used SVM with 12 technical indicators including A/D oscillator, CCI, disparity5, disparity10, momentum, stochastic K%, stochastic D%, stochastic slow D%, Williams' %R, OSCP, ROC and RSI which are used to make up the initial attributes. Analysis of the experimental results has proved that applying SVM in financial prediction by comparing it with a back-propagation neural network (BPN) and case-based reasoning (CBR) is feasible and it is advantageous. Pai and Lin [35], have developed a prediction model integrating ARIMA and SVM models in order to estimate the daily closing prices of ten companies. The hybrid model integrated ARIMA and SVM has been observed to significantly reduce all estimation errors when compared to models using only ARIMA and SVM only. In their study, Huang et al. [2] have investigated weekly movement direction of NIKKEI 225 with SVM by evaluating its performance with those of Elman backpropagation neural networks, linear discriminant analysis, and quadratic discriminant analysis. The findings of the experiment indicate that SVM exhibits better forecasting performance than the other classification methods. Kumar and Thenmozhi [36] in their study have presented SVM and random forest to forecast the direction of the change in the daily stock price in the S&P CNX NIFTY Market Index of the National Stock Exchange by comparing the results with those of the artificial neural network, logit models and discriminant analysis. Their results demonstrated that SVM outperformed the other methods like the random forest, neural networks, and other traditional models. Following year, Kumar and Thenmozhi [37] have examined the feasibility of ANN, ARIMA, SVM, and random forest regression models in forecasting the S&P CNX NIFTY Index return by measuring their performance statistically and financially through a trading experiment which propose that the SVM model demonstrates better performance than other models used in their research. Hsu et al. [38] have developed two-stage architecture by using the self-organizing map and support vector regression with an examination of seven major stock markets to forecast stock prices. The results suggest that the two-stage architecture offers a viable solution for forecasting stock prices. In their studies, Kara et al. [3] have compared the performance of ANN and SVM for the purpose of estimating the ISE-100 Index. For the analysis, the data set covering the closing prices in the period from 2 January 1997-31 December 2007 has been used with selected 10 technical indicators including A/D oscillator, CCI, MACD, momentum, RSI, stochastic K%, stochastic D%, simple moving average (SMA), weighted moving average (WMA) and Williams' %R. Although the results are successful in both methods, it is found that ANN has 75.74% and SVM had 71.52% predictive performance. In another study published at the same year, Ozdemir et al. [39] have estimated the movement direction of the ISE-100 Index return by using both Logistic Regression (LR) and Support Vector Machines (SVM) on monthly data covering the period of February 1997 – December 2010. A total of 167 data sets are divided into 138 data training sets in which the models were installed and 29 data sets of predictions of the validity of the models. According to the results of the study, support vector machines can be used effectively by investors and researchers to predict the stock returns as an alternative method. Tayyar and Tekin [40] have used Support Vector Machines (SVM) to forecast the movement direction of the Istanbul Stock Exchange National 100 Index (ISE-100). They compared the classification performance of SVM with Logistic Regression (LR) method used in this study in order to predict the movement direction of the ISE-100 Index. The analysis includes data sets of 4226 data that have been established daily, weekly and monthly from 03.04.1995 to 19.03.2013. They have built 4 models for each dataset and evaluated index movement direction forecasting performance of these methods by applying different criteria for each model. They observed that the best estimation of the movement direction of ISE-100 Index was in Model 1 (70.0%) among other models with an increase of (82.89%) and a decrease of (54.68%) direction. Yakut et al. [41] have attempted to estimate BIST index value by using feed-forward artificial neural networks and support vector machines methods. They have used the variables such as exchange rates and other countries' exchanges obtained from including America exchange rate of the dollar, overnight websites between 2005-2012 besides three days' values of the BIST index. According to the result, artificial neural networks and support vector machines methods can be used successfully to predict the stock market index.

In recent years, long-short-term memory (LSTM) networks for recurrent networks have been introduced by [42] and have become the cutting-edge models for a variety of machine learning problems. LSTM networks, one of the most powerful deep learning models, have demonstrated great performance in pattern learning tasks, such as speech recognition, human behavior recognition, and handwriting recognition or time series prediction [43-48]. Beside the tasks mentioned above, LSTM networks have been used in many different subjects such as producing musical compositions [49], detecting protein homology without alignment [50], designing a learning system to tie knots in heart surgery [51] and learning nonregular languages [52]. However, having surveyed the literature, it is seen that there have not been many attempts to deploy LSTM in financial market prediction tasks. Giles et al. [53] applied the RNN model to the daily foreign exchange rates forecasting, and gained success in prediction in thorough experiments predicting the direction of change correctly for the next day with an error rate of 47.1%. Through integrating Google's domestic patterns as public mood measures and macroeconomic factors, Xiong et al. [54] have utilized a Long Short-Term Memory neural network to model S&P 500 volatility, with a 24.2% of mean absolute percentage error, outperforming linear Ridge/Lasso and 31% by at least autoregressive GARCH benchmarks. Roondiwala et al. [55] have presented a recurrent neural network (RNN) and Long Short-Term Memory (LSTM) approach to estimate stock market indices. Shen et al. [56] used Bayesian-optimized recurrent neural network-LSTM to estimate the value of the coin, achieving 52% precision. Pang et al. [57] have proposed the deep long-short-term memory neural network (LSMN) with an embedded layer vectorizing the data to forecast the stock market. The results of the experiment indicate that the LSMN model with the embedded layer is state-of-the-art with an accuracy of 57.2% for the Shanghai A-shares composite and 52.4% for an individual stock. Fischer and Krauss [58] have deployed LSTM networks to forecast out-of-sample directional movements for the stakeholders' stocks in the S&P 500 from 1992 until 2015 and they find that LSTM networks outperform memory-free classification approaches with 0.46% of daily returns and a 5.8% of Sharpe Ratio prior to transaction costs.

Machine learning techniques are seen to be used increasingly in financial time series forecasting as an alternative to statistical methods due to their outstanding learning and generalization ability. The main objective of this paper is to predict stock prices in the daily Borsa Istanbul National 100 Index (BIST100) using multilayer perceptron neural networks (MLP), support vector machines (SVM) and long short term memory (LSTM) models. Thus, we collected 9 years of historical data of BIST 100 between 01.01.2010 - 01.01.2019 and used it for the training and validation purposes. From this literature survey, we find that no previous studies have attempted to predict the stock market prices of BIST 100 through all these three above mentioned models. In this study, we aim to fill this research gap by comparing these three models to forecast the stock market prices. The remainder of this paper is organized into 4 sections. Section 2 describes the methodology. Section 3 provides the computational results and finally, section 4 contains the concluding remarks and future research directions.

2. MATERIAL METHOD

In our study, we have collected stock price datasets obtained from BIST (Borsa İstanbul) website https://www.borsaistanbul.com/ana-sayfa for 42 different companies listed in Istanbul Stock Exchange. Each company has daily opening and closing prices which start from 2010 to 2019 for each company.

Figure 1 illustrates Türkiye İş Bankası A.Ş. closing stock price change over the years.

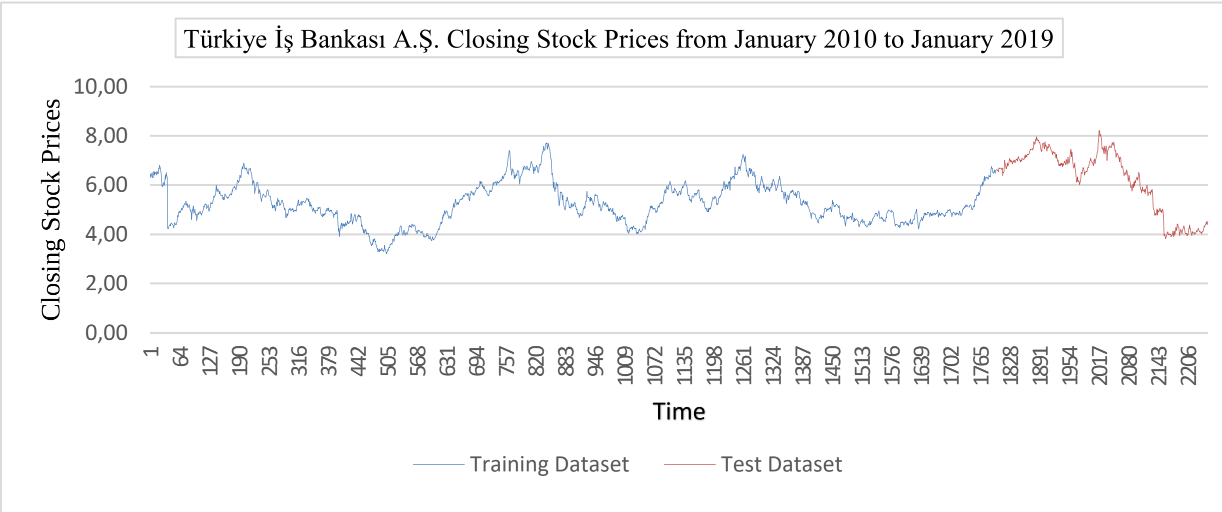

Figure 1. *Türkiye İş Bankası A.Ş. closing stock prices from 2010 to 2019 (2249 days between these dates)*

For the sake of comparison of traditional machine learning algorithms and deep learning models, we chose three different algorithms called Multilayer Perceptrons, Support Vector Machines, Long Short-term Memory (LSTM) which have different mathematical foundations.

Before implementing any machine learning model to a time series dataset, we made some pre-processing as listed below.

- If there is a particular trend, make dataset stationary by subtracting data at the time of t-1 from the data at the time of t.
- Create some lags to make data ready for the time series analysis. We have created lags from 2 to 20 and find the optimum number of lags for each company.
- After implementing the chosen methodologies, reverse data to the original scale.

Each dataset is split as being %80 training and %20 test set and evaluation of the prediction models are made based on the performance on test data. In order to do that, we have used some evaluation metrics given in Table 1.

Table 1. *Evaluation Metrics*

Evaluation Metrics	Formulation
RMSE	$\sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}}$
MSE	$\frac{1}{n}\sum_{i=1}^{n}(y_i - \tilde{y}_i)^2$
R^2	$\left(\frac{\boldsymbol{n}\sum(\boldsymbol{y}\tilde{\boldsymbol{y}}) - \sum \boldsymbol{y} \sum \tilde{\boldsymbol{y}}}{\sqrt{\boldsymbol{n}(\sum \boldsymbol{y}^2) - (\sum \boldsymbol{y})^2} - \sqrt{\boldsymbol{n}\sum(\tilde{\boldsymbol{y}}^2) - (\sum \tilde{\boldsymbol{y}})^2}}\right)^{\boldsymbol{2}}$

2.1. Multilayer Perceptron Algorithm

Artificial Neural Network -also named Multilayer perceptron (MLP)- is one of the machine learning methods to extract the hidden nonlinear relation from the data [59-61]. It consists of some layers called input, hidden, and output as shown in Figure 2.

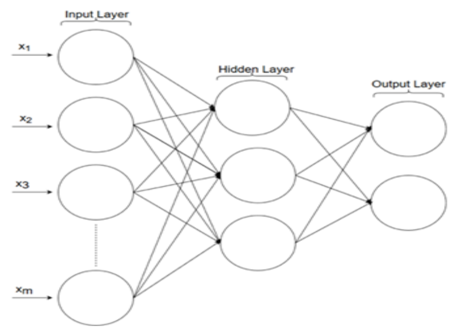

Figure 2. *MLP Structure consisted of Input, Hidden, and Output layers*

Data samples enter the network from input layers, and a linear combination of the values are forwarded to neurons in the next layer. This network process is called as feed-forwarded neural networks. Then the system takes the values from the output layer through the input layer to optimize weights by taking partial derivatives. This method is called backpropagation. The output of n^{th} neuron in l^{th} the layer is calculated based on Equation (1) as the linear combination of the previous layer such that:

$$o = y_l^n = w^T x + b \tag{1}$$

where w^T is the connection weights. The value of each node is transformed by an activation function. There are some available activation functions in the literature. We have used the sigmoid one which transforms the value as being 1 or 0 based on Equation (2)

$$\boldsymbol{\sigma(x)} = \frac{\mathbf{1}}{\mathbf{1}-\boldsymbol{e}^{-(\boldsymbol{w^T x+b})}}. \tag{2}$$

Then, the weights should be adjusted based on Equation (3) to minimize the error for the given dataset.

$$D = \{(x_1, t_1), (x_2, t_2), \dots, (x_d, t_d), .., (x_m, t_m)\}$$

$$\boldsymbol{E}[\overrightarrow{\boldsymbol{w}}] = \frac{\mathbf{1}}{\mathbf{2}} \sum_{\boldsymbol{d \in D}} (\boldsymbol{t_d} - \boldsymbol{o_d}). \tag{3}$$

In order to adjust w_i as $w_i := w_i + \Delta\, w_i$, following partial derivatived procedure should be utilized simultaneously for each w_i as shown in Equation (4)

$$\Delta w_i = -\eta \frac{\partial E}{\partial w_i} \tag{4}$$

where $-\eta$ is the learning rate, Δw_i is the adjustment value. After taking the derivatives, we can wrap up the adjustment rules as shown in Equation (5)

$$\Delta \boldsymbol{w_i} = -\boldsymbol{\eta} \sum_{\boldsymbol{d \in D}} (\boldsymbol{t_d} - \boldsymbol{o_d}) \boldsymbol{x_{id}}. \tag{5}$$

One needs to note that, because our problem is a regression problem, there will be a single neuron in the output layer of the MLP model.

2.2. Support Vector Machines (SVM) Algorithm

Support Vector Machines is one of the widely used machine learning algorithm proposed by [62]. The SVM is initially designed for the binary classification problem, then it is extended for the regression problem [63]. Assume we are given a dataset $\{(x_1, y_2), \ldots, (x_l, y_l)\}$, where each $x_i \in R$ the decision function is given by Equation (6)

$$f(x) = w\phi(x) + b\ . \tag{6}$$

With respect to $w_i \in R$ and } $b \in R$, where ϕ denotes a non-linear transformation from R^n to higher-dimensional space. To make sure $f(x)$ is as flat as possible, magnitude the of the w should be minimized as in Equation (7)

$$J(w) = \frac{1}{2}\|w\|\ . \tag{7}$$

Subject to all residuals having a value less than ε; or, in Equation (8)

$$w\phi(x_i) + b - y_i \leq \varepsilon\ . \tag{8}$$

It is expected that it is impossible to meet this condition for any dataset. So, we can add slack variables ξ^+ and ξ^- to give some flexibility and rewrite the formulations as shown below in Equation (9)

$$J(w) = \frac{1}{2}\|w\| + C\sum_i^n \xi^+ + \xi^-. \tag{9}$$

Subject to:

$$y_i - (w\phi(x_i) + b) \leq \varepsilon + \xi^+$$
$$(w\phi(x_i) + b) - y_i \leq \varepsilon + \xi^-$$
$$\xi^+ \geq 0$$
$$\xi^- \geq 0$$

where C is a constant value that assigns some penalty values imposed to the variables which stay outside the ε margin and help to avoid being overfitting. Finally, we can calculate the loss function that ignores the error if the predicted value is less than or equal to ε . Thus, it can be formulated as shown in Equation (10)

$$\boldsymbol{f(x)} = \begin{cases} \mathbf{0}, & \boldsymbol{if\ w\phi(x_i) + b - y_i \leq \varepsilon} \\ \boldsymbol{|w\phi(x_i) + b - y_i| - \varepsilon}, & \boldsymbol{otherwise} \end{cases}. \tag{10}$$

For the sake of mathematical convenience, the given optimization problem described above can be solved in dual form.

2.3. Long-Short Term Memory Algorithm

Long-Short Term Memory is developed based on a recurrent neural network proposed by [42]. As opposed to a traditional neural network, LSTM network is designed to remember what happened in the past and how this affects the current situation. To make it more concrete assume that we are given a dataset $X = \{x^{<1>}, x^{<2>}, \ldots, x^{<t>}, \ldots, x^{<T_x>}\}$ (i.e X is a sentence and $x^{<t>}$ is the t^{th} word in that sentence). A RNN network takes the information from $x^{<t>}$ and activation value $a^{<t-1>}$from the previous time step to help prediction with $y^{<t>}$. Based on the structure of the RNN we can build the formulation of the RNN as shown in Equations (11) and (12)

$$a^{<t>} = g(W_{aa}a^{<t-1>} + W_{ax}x^{<t>} + b_a) \tag{11}$$

where $a^{<t>}$ is accounts for the activation value in time step t, g is the chosen activation function, W_{aa} is the parameter for the activation values, W_{ax} is parameters for the input values, an b_a is the bias value. The prediction of the corresponding sample $y^{<t>}$can be made based on Equation (12) by using the value of $a^{<t>}$

$$\hat{y}^{<t>} = g(W_{ya}a^{<t>} + b_y) \tag{12}$$

where $W_{ya}a$ is the parameter matrix for the activations and b_y is the bias value.

Optimizing the LSTM network is similar to a traditional neural network. To minimize the overall error of the system as shown in Equation (13) back-propagation algorithm can be used.

$$\boldsymbol{L}(\hat{\boldsymbol{y}}^{<t>}, \boldsymbol{h}^{<t>}) = \sum_{\boldsymbol{t=1}}^{\boldsymbol{T_x}}(\hat{\boldsymbol{y}}^{<t>}, \boldsymbol{y}^{<t>}). \tag{13}$$

In addition to RNN systems, GRU system has an additional component called memory cell based on “remembering” what happened in the past. A simple structure is shown in the following Figure 3.

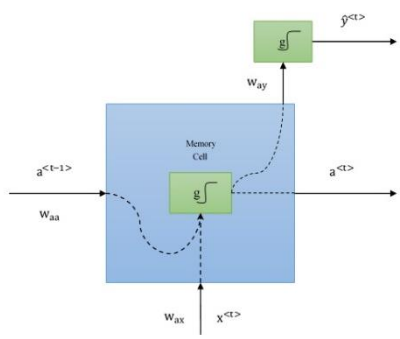

Figure 3. *Simple GRU structure for sequential data*

So, assume that $c^{<t>}$ used instead of $a^{<t>}$is the memory cell works to save some important information. It needs to be decided to change the value of $c^{<t>}$ by first calculating candidate memory cell value $\hat{c}^{<t>}$ as shown in Equation (14)

$$\hat{c}^{<t>} = g(W_{cc}c^{<t-1>} + W_{cx}x^{<t>} + b_c) \tag{14}$$

where g is the activation function, W_{cc} is the parameter for the memory cell values, W_{cx} is the parameter for the input data, and $c^{<t-1>}$ is the memory cell value from the previous time step. We define a parameter Γ_u named as update gate which takes either 1 or 0 meaning "update" and "do not update" respectively in order to update the memory cell value in a correct time. The formulation of Γ_u is as in Equation (15)

$$\Gamma_u = g(W_{uc}c^{<t-1>} + W_{ux}x^{<t>} + b_u) \tag{15}$$

where g is the activation function, W_{uc} and W_{ux} are the parameters for memory cell value and input data respectively during the update step.
Finally $c^{<t>}$ value can be overwritten as in Equation (16)

$$c^{<t>} := \Gamma_u\hat{c}^{<t>} + (1 - \Gamma_u)c^{<t-1>}. \tag{16}$$

In the case of Γ_u is equal to 1, $c^{<t>} = \hat{c}^{<t>}$ meaning that update $c^{<t>}$, otherwise $c^{<t>} = c^{<t>}$ meaning that do not update. Now, we can extend the GRU structure as being an LSTM network. The assumption $c^{<t>} = a^{<t>}$ will be removed and two new parameters Γ_f and Γ_o named as forget gate and output gate respectively will be added. The revised formulation of the LSTM is shown in Equations (17)-(22)

$$\hat{c}^{<t>} = g(W_{ca}a^{<t-1>} + W_{cx}x^{<t>} + b_c) \tag{17}$$
$$\Gamma_u = g(W_{ua}a^{<t-1>} + W_{ux}x^{<t>} + b_u) \tag{18}$$
$$\Gamma_f = g(W_{fa}a^{<t-1>} + W_{fx}x^{<t>} + b_f) \tag{19}$$
$$\Gamma_o = g(W_{oa}a^{<t-1>} + W_{ox}x^{<t>} + b_o) \tag{20}$$
$$c^{<t>} = \Gamma_u \hat{c}^{<t>} + \Gamma_f c^{<t-1>} \tag{21}$$
$$a^{<t>} = \Gamma_o c^{<t>}. \tag{22}$$

Instead of calculating $c^{<t>}$ based on Equation (16), we imply the formula given in Equation (17) and activation $a^{<t>}$ is calculated based on Equation (22) instead of equalling it to $c^{<t>}$. The simple structure of the LSTM cell is shown in Figure 4.

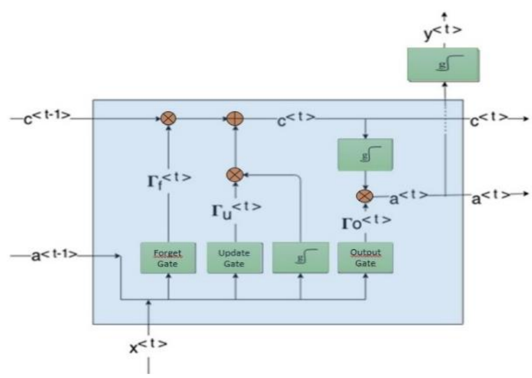

Figure 4. *The structure of LSTM model.* $\otimes$ *= element-wise multiplication and* $\oplus$ *= summation processes*

3. THE RESEARCH FINDINGS AND DISCUSSION

The results of the accuracy measures calculated for the estimates of the models are shown in Table 2.

Table 2. *Results of MLP, SVM, and LSTM models*

	MLP					SVM				LSTM			
	Method		Opening		Closing		Opening		Closing		Opening		Closing
AKBNK	RMSE	Lag2	0,27463	Lag2	0,17431	Lag3	0,31276	Lag2	0,24007	Lag2	0,28089	Lag2	0,17424
	MSE		0,07542		0,03038		0,09782		0,05763		0,07890		0,03036
	R-square		0,96449		0,98588		0,98738		0,99267		0,96291		0,98589
AKSA	RMSE	Lag5	0,90378	Lag3	0,28569	Lag2	1,69791	Lag2	1,61261	Lag6	0,86830	Lag4	0,28526
	MSE		0,81682		0,08162		2,88291		2,60050		0,75394		0,08137
	R-square		0,83902		0,98269		0,79320		0,77006		0,83863		0,98277
ALARK	RMSE	Lag1	0,46026	Lag6	0,16701	Lag2	0,74782	Lag2	0,58869	Lag2	0,41068	Lag6	0,16709
	MSE		0,21184		0,02789		0,55923		0,34655		0,16866		0,02792
	R-square		0,92431		0,99002		0,92489		0,95663		0,93770		0,99001
AEFES	RMSE	Lag3	0,58495	Lag1	0,42600	Lag2	0,59701	Lag1	0,43512	Lag3	0,53085	Lag5	0,42310
	MSE		0,34216		0,18148		0,35642		0,18933		0,28181		0,17902
	R-square		0,94304		0,97033		0,98330		0,99181		0,95248		0,97061
ARCLK	RMSE	Lag1	0,75585	Lag5	0,42596	Lag2	1,60018	Lag1	1,26149	Lag2	0,62609	Lag6	0,33090
	MSE		0,57131		0,18144		2,56058		1,59135		0,39199		0,10949
	R-square		0,96799		0,97034		0,95080		0,97203		0,97796		0,99389
ASELS	RMSE	Lag2	1,59523	Lag1	0,98026	Lag3	7,17062	Lag4	6,49366	Lag5	1,60745	Lag2	0,97990
	MSE		2,54475		0,96091		51,41780		42,16761		2,58390		0,96021
	R-square		0,90443		0,96212		0,10905		0,30025		0,90181		0,96209
BIMAS	RMSE	La	1,61346	La	1,09490	La	1,59721	La	1,36570	La	1,49377	La	1,09323

	MSE		2,60325		1,19881		2,55107		1,86513		2,23134		1,19516
	R-square		0,95155		0,97731		0,98760		0,99030		0,95784		0,97740
DOHOL	RMSE	Lag1	0,04382	Lag4	0,03157	Lag2	0,04856	Lag2	0,03839	Lag4	0,04499	Lag6	0,03150
	MSE		0,00192		0,00100		0,00236		0,00147		0,00202		0,00099
	R-square		0,93516		0,96638		0,97915		0,98668		0,93074		0,96670
DOAS	RMSE	Lag3	0,43450	Lag3	0,13622	Lag3	0,44497	Lag2	0,36828	Lag2	0,34798	Lag4	0,13633
	MSE		0,18879		0,01856		0,19800		0,13563		0,12109		0,01859
	R-square		0,92594		0,99276		0,97615		0,98372		0,95221		0,99275
ECZYT	RMSE	Lag3	0,18222	Lag5	0,08816	Lag2	0,34586	Lag2	0,33619	Lag6	0,16916	Lag2	0,08814
	MSE		0,03321		0,00777		0,11962		0,11302		0,02862		0,00777
	R-square		0,90289		0,97565		0,88959		0,86961		0,90958		0,97563
ENKAI	RMSE	Lag4	0,11063	Lag1	0,08353	Lag6	0,12070	Lag1	0,09202	Lag5	0,09761	Lag4	0,08344
	MSE		0,01224		0,00698		0,01457		0,00847		0,00953		0,00696
	R-square		0,94476		0,96922		0,98224		0,99013		0,95711		0,96927
ERGLI	RMSE	Lag5	0,62450	Lag6	0,21762	Lag1	2,97532	Lag1	2,86993	Lag1	0,62420	Lag4	0,21824
	MSE		0,39000		0,04736		8,85253		8,23647		0,38962		0,04763
	R-square		0,88302		0,98536		-0,34481		-0,27215		0,88258		0,98529
FENER	RMSE	Lag2	2,10802	Lag1	0,86059	Lag1	5,20650	Lag1	8,23015	Lag4	1,88869	Lag5	0,85964
	MSE		4,44374		0,74062		27,10768		67,73531		3,56716		0,73899
	R-square		0,95265		0,99186		0,90069		0,73611		0,96165		0,99188
FROTO	RMSE	Lag5	3,52338	Lag3	1,25739	Lag2	9,87562	Lag1	13,40055	Lag4	3,42740	Lag4	1,25897
	MSE		12,41422		1,58104		97,52794		179,57475		11,74708		1,58500
	R-square		0,85115		0,97974		0,60282		-0,04225		0,85565		0,97966
GSRAY	RMSE	Lag2	13,88379	Lag4	1,10785	Lag2	32,44558	Lag2	26,65017	Lag5	9,86357	Lag1	1,10774
	MSE		192,75972		1,22732		1052,71533		710,23163		97,28993		1,22710
	R-square		-0,02478		0,98478		-1,95721		-2,60928		-0,13029		0,98478
GARAN	RMSE	Lag1	0,29616	Lag3	0,20367	Lag3	0,07923	Lag2	0,31701	Lag3	0,29623	Lag3	0,20241
	MSE		0,08771		0,04148		0,00628		0,10049		0,08775		0,04097
	R-square		0,96250		0,98246		0,75958		0,98786		0,96252		0,98271
GSDHO	RMSE	Lag5	0,08387	Lag4	0,01751	Lag4	0,07923	Lag5	0,04821	Lag6	0,06394	Lag4	0,01749
	MSE		0,00703		0,00031		0,00628		0,00232		0,00409		0,00031
	R-square		0,34252		0,96321		0,75958		0,91500		0,48164		0,96331
GUBRF	RMSE	Lag3	0,89998	Lag4	0,07696	Lag3	1,12782	Lag6	0,80037	Lag5	0,65931	Lag6	0,07664
	MSE		0,80997		0,00592		1,27198		0,64060		0,43470		0,00587
	R-square		0,19014		0,99032		0,43540		0,52902		0,30812		0,99042
HALKB	RMSE	Lag1	0,59764	Lag5	0,24096	Lag2	1,13610	Lag2	1,07685	Lag2	0,52225	Lag5	0,24129
	MSE		0,35717		0,05806		1,29072		1,15960		0,27274		0,05822
	R-square		0,94718		0,99152		0,93686		0,94471		0,95945		0,99150
ISCTR	RMSE	Lag5	0,20884	Lag4	0,12609	Lag6	0,29297	Lag4	0,23080	Lag5	0,19783	Lag3	0,12607
	MSE		0,04361		0,01590		0,08583		0,05327		0,03914		0,01589
	R-square		0,97279		0,99012		0,98455		0,99082		0,97563		0,99013
ISGSY	RMSE	Lag2	0,05672	Lag4	0,01755	Lag6	0,09196	Lag5	0,15950	Lag4	0,04993	Lag2	0,01753
	MSE		0,00322		0,00031		0,00846		0,02544		0,00249		0,00031
	R-square		0,93389		0,99372		0,93975		0,77494		0,94814		0,99374
KRDMD	RMSE	Lag4	0,25388	Lag4	0,10073	Lag1	0,98249	Lag1	0,95262	Lag2	0,25203	Lag4	0,10046
	MSE		0,06445		0,01015		0,96529		0,90749		0,06352		0,01009
	R-square		0,94765		0,99163		0,63021		0,64835		0,94828		0,99168
KARSN	RMSE	Lag4	0,04874	Lag3	0,05036	Lag2	0,05813	Lag2	0,05794	Lag3	0,04889	Lag1	0,05014
	MSE		0,00238		0,00254		0,00338		0,00336		0,00239		0,00251
	R-square		0,97820		0,97631		0,99180		0,99163		0,97808		0,97637
KCHOL	RMSE	Lag4	0,71500	Lag6	0,27121	Lag2	1,51273	Lag1	1,49492	Lag4	0,67628	Lag1	0,27044
	MSE		0,51122		0,07355		2,28835		2,23479		0,45736		0,07314
	R-square		0,77940		0,96498		0,65723		0,60659		0,79324		0,96505
KOZAA	RMSE	Lag2	0,38706	Lag2	0,22504	Lag3	0,82797	Lag3	0,80473	Lag3	0,39341	Lag4	0,22452
	MSE		0,14982		0,05064		0,68554		0,64759		0,15477		0,05041
	R-square		0,94926		0,98257		0,92782		0,92776		0,94722		0,98266
METRO	RMSE	Lag1	0,04854	Lag6	0,02837	Lag3	0,04489	Lag3	0,03158	Lag6	0,04550	Lag3	0,02826
	MSE		0,00236		0,00080		0,00201		0,00100		0,00207		0,00080
	R-square		0,89042		0,96265		0,97626		0,98840		0,90079		0,96317

MGROS	RMSE	Lag3	0,93954	Lag2	0,46614	Lag6	1,05315	Lag3	0,76614	Lag2	0,83635	Lag3	0,46568
	MSE		0,88274		0,21728		1,10911		0,58697		0,69948		0,21686
	R-square		0,96079		0,99056		0,98650		0,99345		0,96878		0,99059
NETAS	RMSE	Lag1	7,77737	Lag6	0,32402	Lag1	7,69263	Lag5	7,77190	Lag6	5,77036	Lag2	0,32366
	MSE		60,48748		0,10499		59,17651		60,40237		33,29710		0,10476
	R-square		-0,62799		0,98871		0,49865		-2,62104		-2,40533		0,98869
PETKM	RMSE	Lag5	0,20671	Lag1	0,13671	Lag2	0,26157	Lag1	0,22806	Lag5	0,20697	Lag1	0,13715
	MSE		0,04273		0,01869		0,06842		0,05201		0,04284		0,01881
	R-square		0,96706		0,98528		0,98591		0,98843		0,96700		0,98520
SAHOL	RMSE	Lag1	0,25282	Lag3	0,15625	Lag3	0,24520	Lag3	0,17673	Lag5	0,24244	Lag5	0,15542
	MSE		0,06392		0,02441		0,06012		0,03123		0,05877		0,02415
	R-square		0,96535		0,98679		0,99148		0,99571		0,96821		0,98691
SISE	RMSE	Lag2	0,26250	Lag6	0,20919	Lag2	0,62501	Lag4	0,42362	Lag4	0,26001	Lag5	0,21045
	MSE		0,06891		0,04376		0,39064		0,17946		0,06761		0,04429
	R-square		0,74140		0,82766		0,28107		0,65576		0,74117		0,82445
TSGYO	RMSE	Lag1	0,10308	Lag2	0,02545	Lag1	0,29031	Lag1	0,20924	Lag5	0,08905	Lag4	0,02544
	MSE		0,01063		0,00065		0,08428		0,04378		0,00793		0,00065
	R-square		0,88816		0,99308		0,65187		0,82113		0,91191		0,99310
TAVHL	RMSE	Lag3	1,19369	Lag5	0,59178	Lag4	2,01652	Lag2	2,02184	Lag5	1,16661	Lag4	0,59295
	MSE		1,42489		0,35021		4,06635		4,08782		1,36098		0,35159
	R-square		0,91663		0,97905		0,92029		0,91248		0,91913		0,97895
TKFEN	RMSE	Lag6	0,94140	Lag1	0,40458	Lag1	7,82695	Lag1	7,46973	Lag4	0,95855	Lag3	0,40448
	MSE		0,88623		0,16369		61,26110		55,79687		0,91881		0,16360
	R-square		0,95289		0,99122		-1,23969		-0,99053		0,95064		0,99123
TOASO	RMSE	Lag2	1,81918	Lag5	0,47735	Lag2	3,08997	Lag3	3,11582	Lag6	1,72115	Lag4	0,47403
	MSE		3,30940		0,22786		9,54790		9,70834		2,96236		0,22471
	R-square		0,85766		0,98974		0,87800		0,83419		0,86375		0,98982
TRKCM	RMSE	Lag1	0,15569	Lag2	0,09227	Lag1	0,55595	Lag2	0,46875	Lag6	0,14212	Lag1	0,09229
	MSE		0,02424		0,00851		0,30908		0,21972		0,02020		0,00852
	R-square		0,92784		0,97408		0,63393		0,73563		0,93835		0,97408
TUPRS	RMSE	Lag4	5,92613	Lag4	2,45314	Lag1	23,51079	Lag1	23,22553	Lag4	6,53149	Lag6	2,44413
	MSE		35,11898		6,01791		552,75745		539,42505		42,66032		5,97379
	R-square		0,81766		0,96634		-0,21035		-0,32792		0,78397		0,96633
THYAO	RMSE	Lag1	0,95290	Lag1	0,70796	Lag1	4,15745	Lag1	4,10337	Lag3	0,91524	Lag1	0,70845
	MSE		0,90802		0,50120		17,28437		16,83765		0,83766		0,50190
	R-square		0,95217		0,97318		0,58631		0,58923		0,95554		0,97314
TTKOM	RMSE	Lag3	0,23473	Lag1	0,11734	Lag1	0,47836	Lag1	0,46584	Lag1	0,23717	Lag3	0,11733
	MSE		0,05510		0,01377		0,22883		0,21700		0,05625		0,01377
	R-square		0,95904		0,98985		0,94111		0,94517		0,95795		0,98985
	RMSE	Lag1	0,29766	Lag2	0,26035	Lag2	0,44667	Lag1	0,43790	Lag5	0,29662	Lag5	0,26003
TCELL	MSE		0,08860		0,06778		0,19951		0,19175		0,08798		0,06761
	R-square		0,95939		0,96857		0,97382		0,97397		0,95945		0,96858
VAKBN	RMSE	Lag4	0,22085	Lag4	0,12277	Lag4	0,29220	Lag4	0,25462	Lag2	0,22263	Lag3	0,12226
	MSE		0,04878		0,01507		0,08538		0,06483		0,04956		0,01495
	R-square		0,96996		0,99076		0,98495		0,98893		0,96948		0,99085
YKBNK	RMSE	Lag1	0,22209	Lag1	0,09537	Lag1	0,42522	Lag1	0,41442	Lag6	0,22301	Lag3	0,09540
	MSE		0,04932		0,00910		0,18081		0,17175		0,04973		0,00910
	R-square		0,96465		0,99353		0,95679		0,95862		0,96453		0,99353

The most important result of the presented measurements is that all measurements show the MLP and LSTM models as the most accurate forecasting models. These results are supported using some basic statistics. Tables (2)-(4) show the basic statistics of forecasting errors. Statistical analyses were performed with the help of IBM SPSS Statistics software and a two-tailed t-test analysis was used to determine whether there was any difference between the groups.

Table 3. *Two-Tailed T-test Results for MLP*

This table reports the statistics for the daily stock prices of the companies listed in BIST100 index (01/01/2010-01/01/2019)												
	Results for Opening Stock Prices						Results for Closing Stock Prices					
Companies	N	Corr.	Sig.	t	df	Sig. (2-tailed)	N	Corr.	Sig.	t	df	Sig. (2-tailed)
AKBNK	449	,982	,000	-,360	448	,719	449	,993	,000	-,003	448	,998
AKSA	449	,920	,000	1,043	448	,297	450	,991	,000	-,593	449	,553
ALARK	449	,962	,000	,369	448	,712	448	,995	,000	-,012	447	,991
AEFES	449	,972	,000	-,753	448	,452	449	,985	,000	-,005	448	,996
ARCLK	449	,984	,000	-,471	448	,638	449	,985	,000	,101	448	,920
ASELS	449	,952	,000	-,322	448	,748	449	,981	,000	,409	448	,683
BIMAS	449	,976	,000	,372	448	,710	449	,989	,000	1,387	448	,166
DOHOL	449	,968	,000	1,062	448	,289	449	,983	,000	,348	448	,728
DOAS	449	,963	,000	,357	448	,721	449	,996	,000	-,324	448	,746
ECZYT	449	,952	,000	1,241	448	,215	449	,988	,000	,094	448	,925
ENKAI	449	,972	,000	-,157	448	,875	449	,985	,000	-,012	448	,991
ERGLI	449	,941	,000	-,149	448	,882	448	,993	,000	,355	447	,723
FENER	449	,977	,000	-,993	448	,321	449	,996	,000	-,088	448	,930
FROTO	449	,925	,000	,167	448	,867	449	,990	,000	,371	448	,711
GSRAY	449	,487	,000	,008	448	,994	449	,992	,000	,008	448	,994
GARAN	449	,981	,000	-,132	448	,895	449	,991	,000	-,164	448	,870
GSDHO	449	,671	,000	,323	448	,747	449	,982	,000	,316	448	,752
GUBRF	449	,596	,000	,007	448	,994	448	,995	,000	,001	447	,999
HALKB	449	,974	,000	-,015	448	,988	449	,996	,000	,642	448	,521
ISCTR	449	,986	,000	-,383	448	,702	449	,995	,000	-,002	448	,998
ISGSY	449	,967	,000	-1,837	448	,067	449	,997	,000	,026	448	,979
KRDMD	449	,974	,000	,229	448	,819	449	,996	,000	,145	448	,885
KARSN	449	,989	,000	-1,166	448	,244	449	,988	,000	-,268	448	,789
KCHOL	449	,890	,000	,001	448	,999	448	,983	,000	-,590	447	,555
KOZAA	449	,975	,000	1,274	448	,203	449	,991	,000	1,240	448	,216
METRO	449	,945	,000	,448	448	,655	448	,981	,000	-,148	447	,883
MGROS	449	,980	,000	,704	448	,482	449	,995	,000	-,274	448	,784
NETAS	449	,187	,000	,004	448	,997	448	,994	,000	,143	447	,886
PETKM	449	,984	,000	,414	448	,679	449	,993	,000	,146	448	,884
SAHOL	449	,983	,000	-,236	448	,814	449	,993	,000	-,584	448	,559
SISE	449	,871	,000	,268	448	,788	448	,914	,000	,024	447	,981
TSGYO	449	,944	,000	-1,347	448	,179	449	,997	,000	-,005	448	,996
TAVHL	449	,958	,000	-,804	448	,422	449	,990	,000	,199	448	,843
TKFEN	448	,976	,000	,910	447	,363	449	,996	,000	,938	448	,349
TOASO	449	,929	,000	,175	448	,861	449	,995	,000	-,179	448	,858
TRKCM	449	,964	,000	,137	448	,891	449	,987	,000	-,008	448	,994
TUPRS	449	,910	,000	-,980	448	,328	449	,983	,000	,209	448	,834
THYAO	449	,976	,000	,733	448	,464	449	,987	,000	,580	448	,562
TTKOM	449	,980	,000	-,177	448	,860	449	,995	,000	,170	448	,865
TCELL	449	,980	,000	-,019	448	,985	449	,984	,000	-,084	448	,933
VAKBN	449	,985	,000	-,501	448	,616	449	,995	,000	-,288	448	,773
YKBNK	449	,982	,000	-,193	448	,847	449	,997	,000	-,107	448	,915

When the t values and P values obtained as a result of the difference analysis between the actual and forecast values of the companies are examined, it is seen that the H_0 hypotheses which support the absence of any difference are supported. In addition, the correlation values also confirm this indifference with values close to 1. The consistency of the predicted values obtained as a result of the MLP analysis was also supported by statistical difference analysis. According to the information obtained from Table 3, the hypotheses established for the MLP model are as follows;

H_0: µ1 to µ2 = 0, H_1: µ1 to µ2 ≠ 0

Opening Prices	*p*-value = Sig. (2-tailed) = 0.650690 Since the p-value = 0.650690> 0.05 = α, the absence hypothesis is accepted.	Closing Prices	*p*-value = Sig. (2-tailed) = 0.798048 Since the p-value = 0.798048> 0.05 = α, the absence hypothesis is accepted.

Table 4. *Two-Tailed T-test Results for SVM*

This table reports the statistics for the daily stock prices of the companies listed in BIST100 index (01/01/2010-01/01/2019)												
	Results for Opening Stock Prices						Results for Closing Stock Prices					
Companies	N	Corr.	Sig.	t	df	Sig. (2-tailed)	N	Corr.	Sig.	t	df	Sig. (2-tailed)
AKBNK	449	,996	,000	7,585	448	,000	449	,998	,000	8,864	448	,000
AKSA	449	,978	,000	25,395	448	,000	450	,997	,000	33,420	449	,000
ALARK	449	,990	,000	4,918	448	,000	450	,999	,000	9,053	449	,000
AEFES	449	,994	,000	3,113	448	,002	450	,996	,000	1,578	449	,115
ARCLK	449	,995	,000	9,986	448	,000	450	,999	,000	17,408	449	,000
ASELS	449	,986	,000	46,057	448	,000	449	,990	,000	48,903	448	,000
BIMAS	449	,994	,000	3,927	448	,000	450	,997	,000	8,208	449	,000
DOHOL	449	,990	,000	3,231	448	,001	449	,994	,000	3,869	448	,000
DOAS	449	,994	,000	-2,230	448	,026	449	,999	,000	5,850	448	,000
ECZYT	449	,989	,000	29,291	448	,000	449	,996	,000	24,452	448	,000
ENKAI	449	,993	,000	9,272	448	,000	450	,996	,000	8,205	449	,000
ERGLI	450	,984	,000	49,738	449	,000	450	,998	,000	52,801	449	,000
FENER	450	,993	,000	-23,727	449	,000	450	,999	,000	-50,404	449	,000
FROTO	449	,981	,000	49,131	448	,000	450	,997	,000	57,502	449	,000
GSRAY	449	,867	,000	-53,655	448	,000	449	,998	,000	-139,394	448	,000
GARAN	449	,994	,000	7,886	448	,000	449	,997	,000	7,087	448	,000
GSDHO	449	,933	,000	-11,423	448	,000	449	,995	,000	-36,323	448	,000
GUBRF	449	,908	,000	-23,317	448	,000	448	,998	,000	-36,094	447	,000
HALKB	449	,994	,000	-18,908	448	,000	449	,998	,000	-23,457	448	,000
ISCTR	449	,997	,000	11,393	448	,000	449	,998	,000	12,315	448	,000
ISGSY	449	,992	,000	-12,565	448	,000	449	,999	,000	-23,074	448	,000
KRDMD	450	,993	,000	25,255	449	,000	450	,999	,000	25,903	449	,000
KARSN	449	,996	,000	2,614	448	,009	449	,997	,000	-6,288	448	,000
KCHOL	449	,975	,000	38,681	448	,000	450	,995	,000	52,421	449	,000
KOZAA	449	,993	,000	27,365	448	,000	449	,996	,000	27,211	448	,000
METRO	449	,988	,000	-3,232	448	,001	449	,995	,000	-7,636	448	,000
MGROS	449	,995	,000	-7,075	448	,000	449	,998	,000	-16,813	448	,000
NETAS	450	,768	,000	-9,310	449	,000	449	,998	,000	-78,313	448	,000
PETKM	449	,996	,000	16,091	448	,000	450	,998	,000	-15,301	449	,000
SAHOL	449	,996	,000	-2,081	448	,038	449	,998	,000	2,194	448	,029
SISE	449	,966	,000	31,914	448	,000	449	,975	,000	17,693	448	,000
TSGYO	450	,985	,000	-35,265	449	,000	450	,999	,000	-30,383	449	,000
TAVHL	449	,986	,000	15,200	448	,000	449	,996	,000	19,488	448	,000
TKFEN	450	,993	,000	42,328	449	,000	450	,999	,000	42,083	449	,000
TOASO	449	,983	,000	28,790	448	,000	449	,996	,000	26,835	448	,000
TRKCM	450	,990	,000	37,150	449	,000	449	,995	,000	33,213	448	,000
TUPRS	450	,970	,000	55,089	449	,000	450	,996	,000	68,724	449	,000
THYAO	450	,994	,000	30,643	449	,000	450	,997	,000	31,174	449	,000
TTKOM	450	,994	,000	-13,613	449	,000	450	,999	,000	-17,802	449	,000
TCELL	449	,994	,000	14,965	448	,000	450	,996	,000	18,816	449	,000
VAKBN	449	,996	,000	8,239	448	,000	449	,998	,000	13,909	448	,000
YKBNK	450	,995	,000	-11,394	449	,000	450	,999	,000	-13,912	449	,000

When the t values and P values obtained as a result of the difference analysis between the actual and forecast values of the companies are examined, it is seen that the H_0 hypotheses which do not show any difference are not supported. The inconsistency of the estimation values obtained as a result of SVM analysis was also supported by statistical difference analysis. The hypotheses established for the SVM model are as follows according to the information obtained from Table 4;

H_0: µ1 to µ2 = 0, H_1: µ1 to µ2 ≠ 0

Opening prices	p-value = Sig. (2-tailed) = 0.001833 Since the p-value = 0.001833 <0.05 = α, the absence hypothesis is rejected.	Closing prices	p-value = Sig. (2-tailed) = 0.003429 Since the p-value = 0.003429 <0.05 = α, the absence hypothesis is rejected.

Table 5. *Two-Tailed T-test Results for LSTM*

This table reports the statistics for the daily stock prices of the companies listed in BIST100 index (01/01/2010-01/01/2019)												
	Results for Opening Stock Prices						Results for Closing Stock Prices					
Companies	N	Corr.	Sig.	t	df	Sig. (2-tailed)	N	Corr.	Sig.	t	df	Sig. (2-tailed)
AKBNK	449	,981	,000	-,139	448	,889	449	,993	,000	,122	448	,903
AKSA	449	,925	,000	-1,538	448	,125	449	,991	,000	-,064	448	,949
ALARK	449	,973	,000	-,553	448	,580	448	,995	,000	-,155	447	,877
AEFES	449	,976	,000	,469	448	,640	449	,985	,000	,073	448	,942
ARCLK	449	,989	,000	,334	448	,738	448	,997	,000	-,660	447	,510
ASELS	449	,951	,000	,584	448	,559	449	,981	,000	,025	448	,980
BIMAS	449	,979	,000	,088	448	,930	449	,989	,000	-,059	448	,953
DOHOL	449	,965	,000	-,410	448	,682	448	,983	,000	,165	447	,869
DOAS	449	,976	,000	,964	448	,336	449	,996	,000	,208	448	,835
ECZYT	448	,958	,000	-,398	447	,691	449	,988	,000	-,001	448	,999
ENKAI	449	,979	,000	,652	448	,515	449	,985	,000	-,067	448	,947
ERGLI	449	,941	,000	,366	448	,715	449	,993	,000	-,115	448	,909
FENER	449	,981	,000	-,379	448	,705	449	,996	,000	,121	448	,904
FROTO	449	,929	,000	1,244	448	,214	449	,990	,000	,129	448	,898
GSRAY	449	,694	,000	-,151	448	,880	449	,992	,000	,204	448	,838
GARAN	449	,981	,000	,452	448	,651	449	,991	,000	,012	448	,990
GSDHO	448	,790	,000	1,678	447	,094	449	,982	,000	-,200	448	,842
GUBRF	449	,757	,000	2,275	448	,023	448	,995	,000	-,079	447	,937
HALKB	449	,980	,000	,652	448	,515	449	,996	,000	,060	448	,952
ISCTR	449	,988	,000	-,314	448	,754	449	,995	,000	,026	448	,979
ISGSY	449	,974	,000	,345	448	,730	449	,997	,000	-,306	448	,760
KRDMD	449	,974	,000	,550	448	,583	449	,996	,000	,066	448	,947
KARSN	449	,989	,000	-,458	448	,647	449	,988	,000	,132	448	,895
KCHOL	449	,900	,000	-,084	448	,933	449	,983	,000	-,212	448	,832
KOZAA	449	,974	,000	,737	448	,461	449	,991	,000	-,028	448	,978
METRO	448	,951	,000	1,258	447	,209	449	,982	,000	,494	448	,622
MGROS	449	,985	,000	-,597	448	,551	449	,995	,000	-,020	448	,984
NETAS	448	,362	,000	-,721	447	,471	449	,994	,000	,243	448	,808
PETKM	449	,983	,000	-,030	448	,976	449	,993	,000	,073	448	,942
SAHOL	449	,984	,000	-,887	448	,376	449	,993	,000	-,339	448	,735
SISE	449	,872	,000	,508	448	,612	449	,913	,000	-,163	448	,871
TSGYO	449	,958	,000	-,325	448	,745	449	,997	,000	-,114	448	,909
TAVHL	449	,960	,000	-,211	448	,833	449	,989	,000	,115	448	,908
TKFEN	449	,976	,000	1,101	448	,272	449	,996	,000	,763	448	,446
TOASO	448	,935	,000	,833	447	,405	449	,995	,000	-1,537	448	,125
TRKCM	448	,970	,000	-2,712	447	,007	449	,987	,000	,160	448	,873
TUPRS	449	,892	,000	,099	448	,921	448	,983	,000	,135	447	,893
THYAO	449	,978	,000	,579	448	,563	449	,987	,000	,346	448	,729
TTKOM	449	,979	,000	-,400	448	,690	449	,995	,000	-,174	448	,862
TCELL	449	,980	,000	,173	448	,862	449	,984	,000	-,202	448	,840
VAKBN	449	,985	,000	,093	448	,926	449	,995	,000	,197	448	,844
YKBNK	448	,982	,000	-,282	447	,778	449	,997	,000	,124	448	,901

When the t values and P values obtained as a result of the difference analysis between the real and forecast values of the companies are examined, it is seen that the H_0 hypotheses which support the absence of any difference are supported. In addition, the correlation values also confirm this indifference with values close to 1. The consistency of the predicted values obtained as a result of LSTM analysis was also supported by statistical difference analysis. The hypotheses established for the LSTM model are as follows according to the information obtained from Table 5;

H_0: $\mu 1$ to $\mu 2 = 0$, H_1: $\mu 1$ to $\mu 2 \neq 0$

Opening prices	p-value = Sig. (2-tailed) = 0.590167 Since the p-value = 0.590167> 0.05 = α, the absence hypothesis is accepted.	Closing prices	p-value = Sig. (2-tailed) = 0.850405 Since the p-value = 0.850405> 0.05 = α, the absence hypothesis is accepted.

4. CONCLUSION

This study attempted to forecast the opening and closing stock prices of 42 firms listed in the Istanbul Stock Exchange National 100 Index (ISE-100) using machine learning methods and deep learning algorithms. For this purpose, two well-known machine learning methods, Multilayer Perceptrons (MLP) and Support Vector Machines (SVM) models and deep learning algorithm, Long Short Term Memory (LSTM) were constructed and applied to the daily data from 2010 to 2019 by comparing their forecasting performances. The analysis includes 9 years of daily data from 01.01.2010 to 01.01.2019. For each firm 2249 data for the opening and 2249 data for the closing stock prices were established as daily data sets which make 188,196 data in total.

Multilayer Perceptrons (MLP) model as a type of artificial neural network method has been applied in many fields and it has been seen that it has achieved successful results in forecasting. The reason why this model has been preferred as an ANN method is that it gives easy, fast, flexible and consistent results. Another model Support Vector Machines (SVM) has been chosen in this study as it has been recently applied successfully in classification, regression and time series forecasting applications. LSTM (Long Short Term Memory) is the last model used in this study as a type of recurrent neural networks designed to recognize patterns in data sequences such as text, genomes, handwriting, spoken word or numerical time series data obtained from sensors, stock markets and government agencies, as it is one the most powerful and useful types of recurrent neural networks. The results show that the MLP model outperforms SVM and LSTM models in predicting the opening stock prices while the LSTM model outperforms MLP and SVM models in predicting the closing stock prices. In predicting both opening and closing stock prices, the SVM model has the worst forecasting performance among other models used in this study. Figure 5. illustrates Türkiye İş Bankası A.Ş. forecasted closing stock prices compared in three models on test dataset.

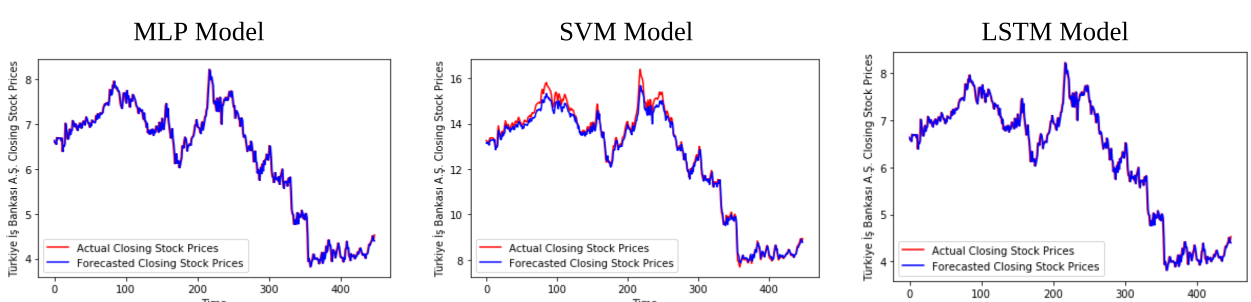

Figure 5. *Türkiye İş Bankası A.Ş. Closing Stock Prices Forecast*

When we look at the statistical measure for goodness-of-fit, it is observed that both MLP and LSTM models have a good fit. As seen in table 6, the MLP model reached the highest (R^2) value (0,831719 %) in opening stock prices and (0,977674%) in closing stock prices; and LSTM model reached the highest (R^2) value

(0,796815%) in opening stock prices and (0,978206 %) in closing stock prices. SVM model reached the lowest (R^2) values for both opening and closing stock prices (0,66195 %, 0,580348 % respectively).

Table 6. *R-squared* (R^2) *Results for MLP, SVM and LSTM Models (Averages)*

	Opening Values	Closing Values
MLP	0,831719	0,977674
SVM	0,661956	0,580348
LSTM	0,796815	0,978206

In this study, two paired t-test was used for the analysis and the Sig (2-Tailed) value which is referred to as the p-value was preferred as 0.005. With a 95% confidence interval, it was revealed that statistically there was no significant difference between the actual values and the forecasted values for both opening and closing stock prices according to the statistical results (Table 7) obtained from MLP and LSTM models.

Table 7. *Two-Tailed T-test Results for MLP, SVM and LSTM Models (Averages)*

	Opening Values	Closing Values
MLP	0,650690 %	0,798048 %
SVM	0,001833 %	0,003429 %
LSTM	0,590167 %	0,850405 %

The hypotheses were established as shown below:

H_0: $\mu 1 - \mu 2 = 0$, H_1: $\mu_1 - \mu_2 \neq 0$

For opening stock prices;

MLP p-value = Sig. (2-tailed) = 0,650690
Since p-value = 0,650690 $>$ 0.05 = α,
we fail to reject the null hypothesis
p-value = Sig. (2-tailed) = 0,001833
SVM Since p-value = 0,001833 $<$ 0.05 = α,
we reject the null hypothesis
LSTM p-value = Sig. (2-tailed) = 0,590167
Since p-value = 0,590167 $>$ 0.05 = α,
we fail to reject the null hypothesis

For closing stock prices;

MLP p-value = Sig. (2-tailed) = 0,798048
Since p-value = 0,798048 $>$ 0.05 = α,
we fail to reject the null hypothesis
SVM p-value = Sig. (2-tailed) = 0,003429
Since p-value = 0,003429 $<$ 0.05 = α,
we reject the null hypothesis
LSTM p-value = Sig. (2-tailed) = 0,850405
Since p-value = 0,850405 $>$ 0.05 = α,
we fail to reject the null hypothesis

Overall, we can say that both MLP and LSTM models are useful in time series for predicting stock prices. However, as opposed to previous studies proposing that SVM is an alternative model for financial time-series forecasting, this study concluded that SVM still needs to be enhanced for prediction applications. The results also showed that the more training cases we use; the better results we get in forecasting time series.

In future studies, it is believed that comparative analysis of MLP and LSTM models with other large scale data collected from various sectors and other methods used in time series forecasting applications will contribute to the literature in determining the effectiveness of MLP and LSTM models. The findings of these additional studies will lead us to several important models of forecasting financial time series.

CONFLICTS OF INTEREST

No conflict of interest was declared by the authors.

REFERENCES

[1] Abu-Mostafa, Y. S., Atiya, A. F., “Introduction to financial forecasting”, Applied Intelligence, 6(3): 205-213, (1996).

[2] Huang, W., Nakamori, Y., Wang S. Y., “Forecasting stock market movement direction with support vector machine”, Computers and Operations Research, 32(10): 2513-2522, (2005).

[3] Kara, Y., Boyacioglu, M. A., Baykan, O. K., “Predicting direction of stock price index movement using artificial neural networks and support vector machines: The sample of the Istanbul Stock Exchange”, Expert Systems with Applications, 38(5): 5311-5319, (2011).

[4] Northover, K., Lo, A. W., “Computational finance”, Computer in Science & Engineering, 1(6): 22, (2000).

[5] Tan, T. Z., Quek, C., Ng, G. S., “Biological brain-inspired genetic complementary learning for stock market and bank failure prediction”, Computer Intelligence, 23(2): 236-261, (2007).

[6] Blank, S. C., “'Chaos' in futures markets? A nonlinear dynamical analysis”, The Journal of Futures Markets, 11(6): 711, (1991).

[7] Zhang, G., Patuwo, B. E., Hu, M. Y., “Forecasting with artificial neural networks: The state of the art” International Journal of Forecasting, 14(1): 35-62, (1998).

[8] Lapedes, A., Farber, R., “Nonlinear signal processing using neural networks: Prediction and system modelling”, 1. IEEE international conference on neural networks, San Diego, CA, USA, No. LA-UR-87-2662; CONF-8706130-4, (1987).

[9] Gorr, W. L., Nagin, D., Szczypula, J., “Comparative study of artificial neural network and statistical models for predicting student grade point averages”, International Journal of Forecasting, 10(1): 17-34, (1994).

[10] Ruiz-Suarez, J., Mayora-Ibarra, O., Torres-Jimenez, J., Ruiz-Suarez, L., “Short-term ozone forecasting by artificial neural networks”, Advances in Engineering Software, 23(3): 143-9, (1995).

[11] Kohzadi, N., Boyd, M. S., Kermanshahi, B., Kaastra, I., “A comparison of artificial neural network and time series models for forecasting commodity prices”, Neurocomputing, 10(2): 169-81, (1996).

[12] Poh, H. L., Yao, J., Jašic, T., “Neural networks for the analysis and forecasting of advertising and promotion impact”, Intelligent Systems in Accounting, Finance and Management, 7(4): 253-68, (1998).

[13] Darbellay, G. A., Slama, M., “Forecasting the short-term demand for electricity: Do neural networks stand a better chance?”, International Journal of Forecasting, 16(1): 71-83, (2000).

[14] Aminian, F., Suarez, E. D., Aminian, M., Walz, D. T., “Forecasting economic data with neural networks”, Computational Economics, 28(1): 71-88, (2006).

[15] Zhuo, W., Li-Min, J., Yong, Q., Yan-Hui, W., “Railway passenger traffic volume prediction based on neural network”, Applied Artificial Intelligence, 21(1): 1-10, (2007).

[16] Yu, L., Wang, S., Lai, K. K., “A neural-network-based nonlinear metamodeling approach to financial time series forecasting”, Applied Soft Computing, 9(2): 563-74, (2009).

[17] Kaastra, I., Boyd, M., “Designing a neural network for forecasting financial and economic time series”, Neurocomputing, 10(3): 215-36, (1996).

[18] Schierholt, K., Dagli, C. H., “Stock market prediction using different neural network classification architectures”, IEEE/IAFE 1996 Conference On Computational Intelligence for Financial Engineering (CIFEr), 72-8, (1996).

[19] Mostafa, M. M., “Forecasting stock exchange movements using neural networks: Empirical evidence from Kuwait”, Expert Systems with Applications, 37(9): 6302-9, (2010).

[20] Naeini, M. P., Taremian, H., Hashemi, H. B., “Stock market value prediction using neural networks”, 2010 International Conference On Computer Information Systems and Industrial Management Applications (CISIM), 132-6, (2010).

[21] Devadoss, A. V., Ligori, T. A. A., “Forecasting of stock prices using multi-layer perceptron”, International Journal of Computing Algorithm, 2: 440-9, (2013).

[22] Kutlu, B., Ozturan, M., Badur, B., “Stock market prediction using artificial neural networks”, Proceedings of the 3rd International Conference on Business, Hawaii, (2003).

[23] Yumlu, S., Gurgen, F. S., Okay, N., “A comparison of global, recurrent and smoothed-piecewise neural models for Istanbul stock exchange (ISE) prediction”, Pattern Recognition Letters, 26(13): 2093-103, (2005).

[24] Guresen, E., Kayakutlu, G., Daim, T. U., “Using artificial neural network models in stock market index prediction” Expert Systems with Applications, 38(8): 10389–97, (2011).

[25] Burges, C. J., “A tutorial on support vector machines for pattern recognition”, Data Mining and Knowledge Discovery, 2(2): 121–67, (1998).

[26] Mukherjee, S., Osuna, E., Girosi, F., “Nonlinear prediction of chaotic time series using support vector machines”, Neural Networks for Signal Processing VII Proceedings of the 1997 IEEE Signal Processing Society Workshop, 511-20, (1997).

[27] Müller, K. R., Smola, A. J., Rätsch, G., Schölkopf, B., Kohlmorgen, J., Vapnik, V., “Predicting time series with support vector machines”, International Conference on Artificial Neural Networks, 999-1004, (1997).

[28] Smola, A. J., Schölkopf, B., “A tutorial on support vector regression”, Statistics and Computing, 14(3): 199-222, (2004).

[29] Vapnik, V., “Statistical learning Theory”, John Wiley and Sons Inc., (1998).

[30] Cao, L., Tay, F. E., “Financial forecasting using support vector machines”, Neural Computing and Applications, 10(2): 184-92, (2001).

[31] Tay, F. E., Cao, L., “Application of support vector machines in financial time series forecasting”, Omega, 29(4): 309-17, (2001).

[32] Tay, F. E., Cao, L., “Improved financial time series forecasting by combining support vector machines with self-organizing feature map”, Intelligent Data Analysis, 5(4): 339-54, (2001).

[33] Tay, F. E., Cao, L., “Modified support vector machines in financial time series forecasting”, Neurocomputing, 48(1-4): 847-61, (2002).

[34] Kim, K., “Financial time series forecasting using support vector machines”, Neurocomputing, 55(1-2): 307-19, (2003).

[35] Pai, P. F., Lin, C. S., “A hybrid ARIMA and support vector machines model in stock price forecasting”, Omega, 33(6): 497-505, (2005).

[36] Kumar M., Thenmozhi M., “Forecasting stock index movement: A comparison of support vector machines and random forest”, 9th Capital Markets Conference, Indian Institute of Capital Markets Paper, (2006).

[37] Kumar, M., Thenmozhi, M., “Support vector machines approach to predict the S&P CNX NIFTY index returns”, 10th Capital Markets Conference, Indian Institute of Capital Markets Paper, (2007).

[38] Hsu, S. H., Hsieh, J. P. A., Chih, T. C., Hsu, K. C., “A two-stage architecture for stock price forecasting by integrating self-organizing map and support vector regression”, Expert Systems with Applications, 36(4): 7947-51, (2009).

[39] Özdemir, A. K., Tolun S., Demirci, “Endeks Getirisi Yönünün İkili Sınıflandırma Yöntemiyle Tahmin Edilmesi: İMKB 100 Endeksi Örneği”, Ömer Halisdemir Üniversitesi İktisadi Ve İdari Bilim Fakültesi Dergisi, 4(2): 45, (2011).

[40] Tayyar, N., Tekin, S., “İMKB-100 endeksinin destek vektör makineleri ile günlük, haftalık ve aylık veriler kullanarak tahmin edilmesi”, Abant İzzet Baysal Üniversitesi Sosyal Bilimler Enstitüsü Dergisi, 13(1): 189-217, (2013).

[41] Yakut, E., Elmas, B., Yavuz, S., “Yapay sinir ağları ve destek vektör makineleri Yöntemleriyle borsa endeksi tahmini”, Süleyman Demirel Üniversitesi İktisadi Ve İdari Bilimler Fakültesi Dergisi, 19(1): 139-57, (2014).

[42] Hochreiter, S., Schmidhuber, J., “Long short-term memory”, Neural Computation, 9(8): 1735-80, (1997).

[43] Baccouche, M., Mamalet, F., Wolf, C., Garcia, C., Baskurt, A., “Sequential deep learning for human action recognition”, International Workshop on Human Behaviour Understanding, 29-39, (2011).

[44] Fernandez, S., Graves, A., Schmidhuber, J., “An application of recurrent neural networks to discriminative keyword spotting”, International Conference on Artificial Neural Networks, 220-9, (2007).

[45] Graves, A., Mohamed, A., Hinton, G., “Speech recognition with deep recurrent neural networks”, 2013 IEEE International Conference on Acoustics, Speech and Signal Processing, 6645-9, (2013).

[46] Graves, A., Schmidhuber, J., “Framewise phoneme classification with bidirectional LSTM and other neural network architectures”, Neural Networks, 18(5-6): 602-10, (2005).

[47] Graves, A., Schmidhuber, J., “Offline handwriting recognition with multidimensional recurrent

neural networks", Advances in Neural Information Processing Systems, 545-52, (2009).

[48] Schmidhuber, J., "Deep learning in neural networks: An overview", Neural Networks, 61: 85-117, (2015).

[49] Eck, D., Schmidhuber, J., "Learning the long-term structure of the blues", International Conference on Artificial Neural Networks, 284-9, (2002).

[50] Hochreiter, S., Heusel, M., Obermayer, K., "Fast model-based protein homology detection without alignment", Bioinformatics, 23(14): 1728-36, (2007).

[51] Mayer, H., Gomez, F., Wierstra, D., Nagy, I., Knoll, A., Schmidhuber, J., "A system for robotic heart surgery that learns to tie knots using recurrent neural networks", Advanced Robotics, 22(13-14): 1521-37, (2008).

[52] Schmidhuber, J., Gers, F., Eck, D., "Learning nonregular languages: A comparison of simple recurrent networks and LSTM", Neural Computation, 14(9): 2039-41, (2002).

[53] Giles, C. L., Lawrence, S., Tsoi, A. C., "Noisy time series prediction using recurrent neural networks and grammatical inference", Machine Learning, 44(1-2): 161-83, (2001).

[54] Xiong, R., Nichols, E. P., Shen, Y., "Deep learning stock volatility with google domestic trends" ArXiv Prepr ArXiv151204916, (2015).

[55] Roondiwala, M., Patel, H., Varma, S., "Predicting stock prices using LSTM", International Journal of Science and Research, 6(4): 1754-6, (2015).

[56] Shen, F., Chao, J., Zhao, J., "Forecasting exchange rate using deep belief networks and conjugate gradient method", Neurocomputing, 167: 243-53, (2015).

[57] Pang, X. W., Zhou, Y., Wang, P., Lin W., Chang, V., "Stock market prediction based on deep long short term memory neural network", Complexis, 102-8, (2018).

[58] Fischer, T., Krauss, C., "Deep learning with long short-term memory networks for financial market predictions", European Journal of Operational Research, 270(2): 654-69, (2018).

[59] Kohonen, T., "An introduction to neural computing", Neural Networks, 1(1): 3-16, (1988).

[60] Lippmann, R. P., "An introduction to computing with neural nets", Artificial Neural Networks: Theoretical Concepts, 36–54, (1988).

[61] Rumelhart, D. E., McClelland, J. L., Group, P. R., "Parallel distributed processing: Exploration in the microstructure of cognition, Vol. 1", (1986).

[62] Cortes, C., Vapnik, V., "Support-vector networks", Machine Learning, 20(3): 273-97, (1995).

[63] Vapnik, V., Golowich, S. E., Smola, A. J., "Support vector method for function approximation, regression estimation and signal processing", Advances in Neural Information Processing Systems, 281-7, (1997).