Deep Learning Based Regression Approach for Algorithmic Stock Trading: A Case Study of the Bist30

Algoritmik İşlemler İçin Derin Öğrenme Tabanlı Regresyon Yaklaşımı: BİST30 Örneği

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Abstract

Today, one of the common uses of artificial intelligence is financial markets. In these markets, which are known as stock market, making price predictions for the future using machine learning and deep learning, making the rise and fall forecasts of indices, sectors and stocks are the main approaches used in this field. In the near future in the financial markets, artificial intelligence based software robots are expected to operate instead of people. For this purpose, learning models are developed by using trend and stock price movements. Validation studies such as accuracy, error value and portfolio simulation are performed to demonstrate the performance of the developed models. In this study, a regression model using deep learning was developed to make adaptive buy-sell operations on the time series consisting of closing prices using data from Borsa İstanbul (BIST). The 2006-2015 range of the BIST30 index was used for training, the 2015-2018 range was used for testing, and the model portfolio value gained 39% on the test data for 694 trading days and the trend direction was estimated with 82% accuracy.

Keywords: Bist, Deep Learning, LSTM, Stock Markets

Öz

Günümüzde yapay zekânın yaygın kullanım alanlarından bir tanesi de finans piyasalarıdır. Kısa adı borsa olarak bilinen bu piyasalarda makine öğrenmesi ve derin öğrenme kullanılarak geleceğe yönelik fiyat tahminleri yapmak, endeks, sektör ve hisse senetlerinin yükseliş ve düşüş öngörülerinin yapılması bu alanda kullanılan temel yaklaşımlardır. Dünya genelinde finans piyasalarında yakın bir gelecekte yapay zekâ temelli yazılım robotlarının insanlar yerine işlem yapması öngörülmektedir. Bu amaçla gerçekleştirilen çalışmalarda endeks ve hisse senedi fiyat hareketleri kullanılarak öğrenme modelleri geliştirilmektedir. Geliştirilen modellerin başarımlarını göstermek için doğruluk, hata değeri ve portföy simülasyonu gibi doğrulama çalışmaları yapılmaktadır. Bu çalışmada, Borsa İstanbul'a (BİST) ait veriler kullanılarak kapanış fiyatlarından oluşan zaman serisi üzerinde adaptif al-sat işlemi yapılması için derin öğrenme kullanan bir regresyon modeli geliştirilmiştir. BİST30 endeksinin 2006-2015 aralığı eğitim, 2015-2018 aralığı ise test için kullanılmış ve 694 işlem gününe ait test verileri üzerinde model portföy değeri %39 değer kazanmış ve trend yönü %82 doğrulukla tahmin edilmiştir.

Anahtar kelimeler: *Bist, Derin Öğrenme, LSTM, Borsa*

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1. Introduction

Financial markets are one of the areas where artificial intelligence is widely applied. Instruments such as stocks, commodities, foreign currency, cryptocurrencies, warrants and derivatives are traded in these markets, which bring buyers and sellers together and work with the principle of taking commission from the buy-sell transactions. It is one of the most valuable and interesting topics in the financial sector to predict which direction the instruments will move in the future (short, medium, long such as daily, weekly, yearly), the timing of this movement and the magnitude of the change using artificial intelligence (Chong et al., 2014).

The purchase / sales price levels of each share traded at the stock exchange are determined as per the threshold values and a commission deduction is made inversely proportional to the transaction volume created. Due to this principle used in determining the tier prices, the investor who invests in any stock can make a profit even as the share price increases by 1 tier as intended. In order for the investor to earn in the stock market, stock prices should move upwards. In addition to this, in the futures option exchange, short-selling type futures can generate earnings in the downward direction of the stock. In the short sale transaction, it is foreseen that the price of the instrument will decrease, if it increases, the investor will suffer. In this way, investors are able to obtain a very significant amount of profit/loss depending on the transaction volume with an instrument falling or rising to a single level. Therefore, it is necessary to have the most suitable share and leverage ratio in order to maximize profit in the direction of bullish (bull market), minimize loss in the direction of decrease (bear market), and short-term transactions in higher risk transactions (Borsa İstanbul., 2020).

Before making an investment decision in financial markets, some analysis should be done systematically. These analysis methods are examined under two main groups as basic and technical analysis. The basic analysis is divided into two groups, PEST and SWOT. In PEST analysis, which consists of the initials of the words Political, Economic, Social and Commercial, the aim is to determine the sector group that will create value, increase profitability and remain bright. SWOT analysis, consisting of the initials of Strengths, Weakness, Opportunities and Threats, covers the strategies to be used to identify companies in the sector where PEST analysis is performed. In addition, economic data of that company such as balance sheet, volume, MV/BV (Market value / Book value) are also used. After PEST and SWOT analysis, stocks that will create value in the future can be determined. However, the basic analysis does not provide sufficient information about its timing (Singh et al., 2018).

For this purpose, technical analysis is carried out using time series formed by price movements. Technical analysis is carried out on the price series, which are formed when the opening and closing, including the specific period for the index and / or stock, are combined with time information using the highest, lowest prices, and the transaction amount (volume). The period mentioned here can be instant, minute, 5 minute, hourly, daily, weekly and monthly. It provides predictions for intraday or short / medium / long term transactions of the selected period analysis. Software-based robots, called "algorithmic transactions", which mostly work as rule-based in financial markets, mostly aim to make profit through transactions that are aimed to stay in the trend direction and are performed during the day or mid-term periods (Cartea et al., 2016).

The technical analysis process can be carried out with the short-term target as mentioned above, or it aims to generate profit in the medium and long term by creating target price and time forecasts. There are many packages and online tools with graphical user interfaces for the use of investors and technical analysts for technical analysis. These tools offer opportunities such as indicator and drawing (trend) tools used in technical analysis and price alarm level identification on time series. BIST publishes instant data for a fee, and data with a delay of 15 minutes is free. For this purpose, package programs and online tools such as Matrix, Tradingview, investing and tradingview can be used. In the following section, the indicators used in the technical analysis process are examined. (Matriks., 2020; Investing., 2020; Tradingview., 2020).

2. Technical Analysis

The technical analysis process of stocks and index prices traded at the stock exchange using time series is analyzed in four main groups as follows (Chiang., 2016).

- **Trend:** It shows the current trend. The trend in which prices are on the rise is called "bull", while the trend in which prices are on

the rise is called "bear". When the market is stagnant, there is horizontal movement.

- **Momentum:** It shows in which direction the prices are trending in the future according to the selected period.

- **Volatility:** It shows the volatility that occurred in price movements.
- **Volume:** They measure the strength of the trend by interpreting the amount of transactions performed with other data along with other indicators.

a) Area chart

b) Bar xhart

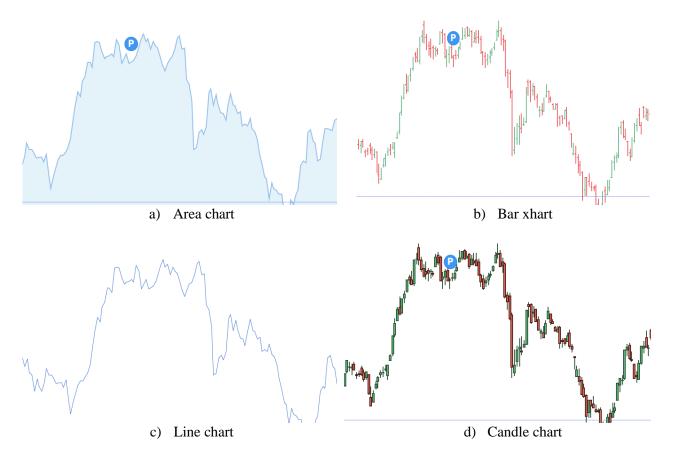c) Line chart

d) Candle chart

Figure 1. Graphical representation of BIST100 index (a) area, (b) bar, (c) line and (d) candle based on daily closings (Investing., 2020).

In Figure 1, the time series graph types formed with index price movements are given. In the figure, the area, line and candle charts created using 1 day closing information are given in sequence. Especially candle charts are widely used in the literature as they provide important clues about the continuation of the current trend and trend returns (Qiu., 2019). In a certain period, opening, highest, lowest, closing prices are obtained by consolidating it as in Figure 1.c and converted into a single chart that can express all of them at the same time. The candle is displayed in blue if the opening price is lower than closing, and in red if low. Hundreds of candlestick chart formations can occur with body / shadow length, length, proportions to each other, colors, shadowless / non-body, and alternating in pairs/triples with periodic closures (Dicle., 2019).

There are more than 70 indicator types, which are analyzed in 4 main groups based on Trend,

Momentum, Volatility and Volume from the movements of stock prices in a certain period. Some of the most commonly used indicators was given as follows with their general logic.

Simple moving average (SMA) gives the simple arithmetical average of prices in the selected period range as given in "1". The more commonly used moving average or exponential moving average, on the other hand, is based on the principle of weighing closings closer to the simple average, as given in "2". The moving average convergence / divergence indicator (MACD) is obtained by subtracting the 12-day exponential moving average from the 26-day exponential moving average, as given in "3". The convergence and divergence of the short-term trend and the long-term trend are important in terms of interpretation. The relative power index (RSI) is an overbought / sell oscillator normalized to the 0-100 range. The "AU_n" given in "4" is the average

of higher closings than the current price in the selected period, and AD_n is the average of lower closings. Together with the RSI, MACD, they are widely used to detect trend continuation power, price action mismatches and trend returns. Finally, as given in Momentum "5", it measures the speed of the instrument in the direction of increase or decrease by taking the difference of the closing price and the closing price in a certain period. Moving Average and Momentum based indicators are widely used in detecting formations such as gold / deadly intersection. 70+ indicator / oscillator values used in technical analysis are not fixed and can be varied according to the parameters and period to be selected. For example, for the trend estimation in indices and stocks, it can be selected from Very Short: 5-14, Short: 14-21, Medium: 21-50, Long: 50-100, Very Long: 100-200. These parameters can be selected in minutes for very short intraday (hourly, daily) buy-sell transactions. In these and similar situations, there is a large number of data in combination (Sezer., 2020).

$$SMA = \frac{\sum_{i=1}^{n} A_i}{n} \tag{1}$$

$$EMA = V * \left(\frac{s}{1+d}\right) + MA * (1 - (\frac{s}{1+d})) \tag{2}$$

$$MACD = MA_{26} - MA_{12} \tag{3}$$

$$RSI = 100 - \left(\frac{100}{1+RS}\right), RS = \frac{AU_n}{AD_n} \tag{4}$$

$$Momentum = A_t - A_w \tag{5}$$

Technical analysis indicators, which are expressed briefly as an indicator above, are divided into two main groups as indicator and oscillator.

- **Indicator:** These are regression models that contain clues about direction changes in technical analysis. For example SMA and EMA given in "2" are indicators.
- **Oscillator:** Regulations, returns and mismatches in the current trend are indicators that have been normalized to a certain range used in determining. For example, MACD and RSI given in "3" and "4" are oscillators.

Below are the exponential moving averages and current candlestick charts of 9 and 50 days based on 5-minute closings for the BIST100 index in Figure 2. Here, the closer 9-day EMA cut the further 50-day EMA upwards. As can be seen from the figure, the indicators give a clue about the future trend by measuring the strength and direction of the trend in selected periods by creating a regression model

Figure 2. EMAs of 9 and 50 days based on daily closings for the BIST100 index (Investing., 2020).

In Figure 3, the index values are shown in red and 50 days EMA are shown green. The RSI oscillator operating in the 0-100 reference range is given below. When interpreting the oscillators, *t* and *t+1* changes in time become important. This is crucial in technical analysis, whether raw price rises / decreases are supported by the oscillator, thereby enabling to identify negative / positive mismatches known as bear / bull traps in the stock market. The "Buy" signal is received when the RSI oscillator 0-30 range cuts the "over-sell" zone upwards, and the "Sell" signal is received when the 70-100 range cuts the "over-purchase" zone downward. The average indicator works similarly. If the current price cuts the indicator value upwards, the "Buy" signal is received, and if it cuts down, the "Sell" signal is received. In general, indicator values are variable as they are obtained by price movements. Oscillator values are composed of values that are normalized to a certain range. In Figure 3, the sample "Buy" signals produced by both the average indicator and the RSI oscillator are indicated by the green arrow and the "Sell" signals by the red arrow.

Figure 3. 50 days EMA and RSI (Investing., 2016).

Main methods used for financial analysis was given in Table 1.

Table 1. Main methods used for financial analysis

Analysis Method	Group	Brief Summary	Method
Fundamental analysis	PEST	Sector analysis	Microeconomic, macroeconomic and global and data-driven
	SWOT	Companies in the sector analysis	
Technical analysis	Time series	They are formed according to the movements of prices in certain periods.	Charts
	Candle, bar charts	The lowest, highest, opening and closing prices of the prices in the period are created by consolidating.	Rule-based
	Indicators Oscillator	They are obtained with mathematical formulas.	Linear regression on price time series
	Trend patterns	They are graphical patterns.	Rule-based, particle wave transformation, image processing and nonlinear methods on time series

3. Literature Review

The literature summary given below covers the studies especially for BIST operating in our country.

A four-layer artificial neural network (ANN) model was created for the index estimation, which takes daily closing values, dollar and overnight interest value as input data between 2001-2006, generating a regression at the output. The error rate between the regression created and the actual value of the index was used to verify the model. The 1143-day data in the selected period was divided into 9: 1 training: test ratio, and the moving average and the method used in the study were compared. In the index trend direction estimation, while the moving average indicator with 50 days of test data provides an accuracy of 50.4%, the approach presented in the study provided an accuracy of 55.1% (Kutlu., 2009).

In order to estimate the stock trend, a dataset containing 15 minutes of closing data for BIST 2013 was used in an approach based on the relational exchange network. 24 stocks selected from the telecommunication, banking and IT sectors were used for the study. In the study, 11 technical indicator data such as RSI, MACD were used by normalizing to 0-1 range. A relationship model has been created that shows the relationship between stocks using a total of 34 attributes obtained using 11 technical indicators along with the trading volume. Macro average F_1 meausre ranging from 0.55 to 1.0 for 24 selected stocks (Ergür., 2013, 2014).

In order to estimate the stock direction, a trend estimation was made using an ANN model with 7 hidden layers, using the daily closing prices of stocks in the period of 2018-2019 in the 24-month period. The data set is divided into 7: 1.5: 1.5 ratio (training: test: validation). In the study, the values obtained from RSI and MACD indicators are categorized as "1": Buy, "-1": Sell and given as an introduction to ANN. The YSA network, which has a single output, performs a Buy or Sell two-class classifier transaction for the relevant stock. In the study, it was found that 3.5% loss was done on the verification data with RSI and MACD, while the developed model gained 2.85% and the proposed model worked more accurately than RSI and MACD (Irmak., 2019).

In BIST and cryptocurrency exchanges, it is aimed to obtain maximum income with minimum risk by making portfolio optimization by using average variance genetic algorithm and particle herd optimization algorithms. For verification, 15 different portfolios were created, and risk, return, sharpe and change coefficients were calculated for the created portfolios. In the portfolio profit and loss simulation, 6.8% - 7.6% profit was obtained with the genetic algorithm, 4.6% - 8.8% profit was obtained with the particle herd algorithm. For 25 stocks containing a 60-week period, a profit of 3.3% - 3.6% was achieved with the genetic algorithm, 3.1% - 5.5% with particle flock optimization (Uluçay., 2019).

For the BİST100, the dataset covering the 18-month period between 2014-2015 was compared the machine learning methods for 1, 2, 5 and 10-day trend estimation. In the study, 10 technical indicator data such as RSI, ROC, Bollinger Bands were used for different machine learning models. Models using ANN, LSTM (Long short term memory), KNN (K nearest neighbor), SVR (Support vector machines), RF (Random forest)

and DT (Decision tree) using Python programming language and Keras library were compared using RMSE error value. In the findings obtained, it was seen that the lowest error was obtained with SVR in general (Ziyadoğlu., 2018).

It has developed a text processing based approach to estimate BIST index direction with economic news. For this purpose, it has collected 111,587 news documents from microblogging sources such as public disclosure platform (KAP) and bigpara between 2010-2011. An approach using natural language processing has been developed with index opening, closing and transaction volume information belonging to the same period. After using useless word detection on text data and transformation of the feature vector, emotion classification was made with Naive Bayes. As a result, it was observed that the use of news and price attributes together did not lead to an improvement in the performance of the index direction. However, it was observed that there was an improvement in the performance of the days when the index was horizontal with news attributes. In the study, the most frequent words in the news of the days when the index rose and decreased were determined and word representations were created (Gündüz., 2013).

Adaptive network-based fuzzy inference system (ANFIS) has been developed the moving average information for the BIST100 index in the 2007-2008 range an early warning system for predicting possible collapse in the stock market with price variability. The ANFIS model obtained the best results in empirical findings such as sensitivity, acuity, Fölçüt compared to ANN, linear regression and bayesian networks used in the study. The findings obtained in the study were also turned into an international book chapter (Acar., 2010; Acar., 2013).

In the thesis study conducted for Bayes theorem and predicting the index direction with ANN, a rule-based expert system and machine learning model was created. The expert system consists of 21 if-then rules. The rule-based system is a system that does not wait until it meets any of the 21 rules, it feels 1000 dollars when the rule is encountered and sells at the end of the period. In the period between January 1, 2007 and April 25, 2008, it made 25% profit. In this process, due to the waiting time of 10-15 days, this profit was achieved with a total of 17 transactions. When the rules were changed to a one-day waiting period, 88 transactions were made and nearly 40% profit

was achieved, but the profit rate per transaction decreased. When the waiting period was changed to 2 days without changing the rules, 215 transactions were made and nearly 50% profit was achieved. When the waiting period was changed as 1 week, a very close success rate was obtained. In the developed ANN model, 5 technical indicator data were used as input, and 250 rounds of training were carried out with a hidden layer of 20 neurons. Based on the amount of profit per transaction, higher success was achieved from the ANN expert system (Bahadır., 2018).

An approach has been developed to find a correlation between text mining and emotion analysis. Within the scope of the study, a total of 14,018 news items related to BIST30 companies were compiled with a robot software. When the news was eliminated that is not related to the economy, a collection was created with 8434 news items. The word roots in the complex have been obtained, useless words such as conjunction that can be accepted as noise have been removed and the positive and negative scores have been calculated on the matrix by converting the words into document-term matrix using the R programming language. 65% of these news are positive news. Within the scope of the thesis, there is a 0.85 correlation between the companies except the companies with little news about BIST30 and the market values and the news; With the news numbers and positive news scores, it is predicted that it can help predict future market value value. The study results were also published in an international refereed journal (Atan., 2016; Atan., 2019).

An application was made on the prediction of stock market index direction using ANN and support vector machines (SVM). In the study, 11 technical indicator values, index change rates and macroeconomic indicators for the period 2005-2011 were used as input data. The 2005-2009 range of this data set was used for training, and the 2009-2011 range was used for testing. The best 80% accuracy was achieved with 11 technical indicators. When 18 global stock market index information was added to this data set, it was 57.2%, and 5 macroeconomic data was added as 54.4%. When the whole data set is combined, an accuracy value of 73.7% was obtained with 34 input data. In order to obtain the highest accuracy rate with the lowest input data, the optimum inputs were 83.5% when 6 technical indicator data, 1 stock index and 1 macroeconomic data were used. Compared to SVM, ANN results were more satisfactory. The findings obtained in the

study were published as articles in an international refereed journal. SVM for BİST100 was used in an international journal study published within the scope of the thesis. Grid search algorithm is used to determine the most suitable parameters in SVM (Emir., 2013).

In his thesis study entitled A predictive ANN approach in financial decision making, he used the data set for BIST100 covering the 80-200 period between 2002-2008. In the study, the closing value of the index, the gold index and the dollar / ₺ parity change were used. This data set was divided into 7:2:1 ratio and training and testing were performed. A multi-layered neural network (MLP) with 7 hidden layers was used for the training process and the net weights were trained using the back propagation algorithm. In the training process, it was obtained with 0.003 MSE error value and 54.4% index prediction accuracy. When the developed model was compared with nonlinear regression and multiple linear regression, an accuracy value of 52% was obtained with nonlinear regression and 42% with multiple linear regression. In the study, it was found that MLP approach gives better results than both regression models and when the regression models are compared within themselves, non-linear regression model gives better results than linear regression (Görgün., 2008).

For the future prediction of BİST30, the deep learning model model was developed by using the 36-month period data set for the 2016-2018 interval. The data set is divided into 8: 2 for training: testing purposes. MSE error value ranging from 0.03 to 0.27 was obtained during the validation phase covering the 5-day period. In the study, 15 technical indicator values were used as input data. In the proposed deep learning model, 7 hidden layers were used and 2 layers were pruned randomly. The only output layer in the network is a two-class classifier that predicts rise or fall. The results of the study have been turned into an international journal study (Raşo., 2019).

In the master thesis study, which examined the effect of price estimates by integrating emotion analysis in stock prices, BIST 2010-2018 period 1659 days period was used for training and 233 days period for testing. For textual data, microblogging source made comments on the market by pulling emotion classification on these data. 4 technical indicator data such as emotion classification and MACD, RSI were used as input in LSTM model. In the output layer of the LSTM model, the RELU activation function performed a

two-label classification process. In the study, it was proved that the emotion classification on the comments on the market was effective in predicting the index direction by obtaining an accuracy of 56% with the network matrix, which was trained only with technical indicators, and 66% with the model including the emotion classification results. In this respect, similar but different findings were obtained with the main purpose of the study (Gündüz., 2013). It has been interpreted that this situation is the developed model, the period of the data set used and its use in technical indicators in this model (Gümüş., 2019).

A new exponential smoothing technique has been developed by using autoregressive changing variance (GARCH) for deep learning and stock trading. In the study, BIST has been used as a data set for a period of 1 year since 2013. The regression model presented in the study was tested in short periods such as 2 weeks and better results were obtained than RSI, MACD and ATR oscillators (Karaoğlu., 2018).

In master thesis study for stock trend prediction, he compared linear regression and ANN model accuracy for BIST30 shares. The linear regression model was better in 1 stock, mostly the ANN model achieved satisfactory better results (Şenol., 2018).

GARCH and ANN models were compared to model variance on time series data. Compared to the GARCH model, better results were achieved with ANN (Yümlü., 2018).

A hybrid model developed by integrating a 6-month data set for 2018 and 10 technical indicator data and depth information (status of orders that determine momentarily for share purchase / sale) and F_1 measure with the model using only technical indicator data in 15-minute periods. F_1 value improved from 0.39 to 0.51 (Taburoğlu., 2019).

In WEKA environment, data mining approaches and linear models used for stock movements were compared. A 5-year data set was used in the study. The best results in the study were obtained with "M5Rules" linear regression. The fastest running algorithm is linear regression (Erguvan., 2018).

In the master thesis, which was carried out with the aim of the economic news covering the 12-month period of 2014, on the closing of the index and the direction of the day, profit was obtained from the profit and loss simulation processes performed in the selected test periods. In the study, the most frequent words were determined by making frequency measurements of the words in the economic news according to the horizontal, rise and fall conditions of the index (Özer., 2015).

In the study, which examined the effects on two stocks by making emotion classification on the text comments on the microblog resource about 17 months of data set and twit for the period of 2014-2018, the success of the classification algorithm in the test period is achieved 95% from 67% (Çelikel., 2018).

In the doctoral thesis study, deep learning approaches were developed for index prediction in Dow Jones (USA) stock exchange. Sezer (2019) has divided the time series data set of Dow Jones shares into 5 years of training and 1 year of testing. Within the scope of the thesis, 4 different approaches are proposed. In the first model, it was developed using the big data frame software "Apache Spark" to predict stock future movements by using ANN. In the second approach, a deep learning network was developed instead of GPP to optimize the RSI oscillator in rising and falling market conditions.
In the third model, estimation was made on 2D images obtained using sliding window and convolutional neural network (CNN) on price time series bar graphs. This approach also brought in a new methodology for the literature in terms of making financial data with image processing rather than temporal analysis. In the last model, with this developed approach, financial prediction has been made with image processing using CNN. Findings obtained in the study are two of them are a review article that systematically compares deep learning algorithms in international financial markets, while others are original studies obtained within the scope of the thesis (Sezer., 2017-2020).

When the literature studies are summarized, the approaches developed have been verified by using classification, accuracy rates and error values with data covering different periods. Better results were obtained on relatively short test data. The biggest reason for this is that price and trend estimation is more difficult due to the volatility in financial markets. Generally, regression and trend direction classifications were made by using time series historical data. In this context, besides the time series and technical indicator data, it is possible to say that more successful results are obtained with hybrid approaches.

4. Materials and Method

In this study, a regression model was developed for deep learning based price prediction using BIST30 daily closing data. In the study, BIST30 index between 2006-2018 was used. The period of these data for the years 2015-2018 was not used in the training process to verify the model. Traditional machine learning algorithms produce an output according to the values obtained from instant inputs. Repetitive neural networks (RNN) can also use the network's previous outputs as input again. Due to these features, they are more effective on time dependent data such as time series, text, video processing. Besides these advantages, RNNs can reveal gradient problems. This disadvantage is realized as the gradient value grows excessively away from the optimum value or disappears by getting very close to zero (Zaremba et al., 2014). To eliminate these disadvantages, it is a solution to use nonlinear activation functions such as threshold or RELU at the network output (Hochreiter and Schmidhuber.,

1997). RNNs also developed the LSTM algorithm that solves the gradient problems experienced. As a result, in this study, a leading price estimation study was carried out on BIST30 data using a 4-layer LSTM. The block diagram of the proposed approach is given in Figure 4.

LSTMs given in Figure 4 contain memory blocks instead of neurons used in ANNs. As shown in the figure, an LSTM structure consists of a memory cell (c_t) and 3 doors, the entrance door (i_t), the exit door (o_t) and the forgetting door (g_t). X_t and h_t is the entry and hidden state at t. Equation "6-11" given U, W weight and b is bias values (Kim et al., 1997).
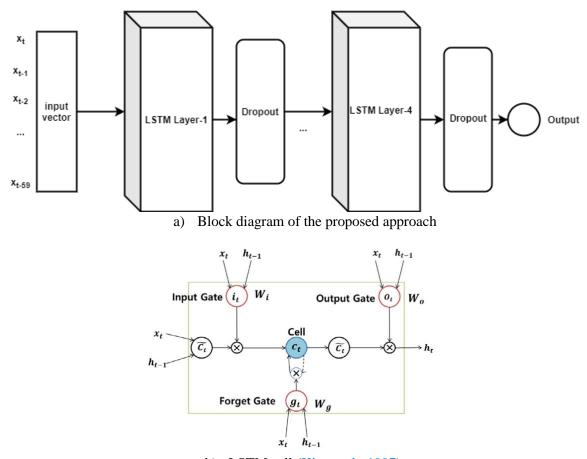
$$g_t = \sigma(U_g x + W_g h_{t-1} + b_f) \tag{6}$$
$$i_t = \sigma(U_i x_t + W_i h_{t-1} + b_i) \tag{7}$$
$$\tilde{c}_t = tanh(U_c X_t + W_c h_{t-1} + b_c) \tag{8}$$
$$c_t = g_t * c_{t-1} + i_t * \tilde{c}_t \tag{9}$$
$$o_t = \sigma(U_o x_t + W_o h_{t-1} + b_o) \tag{10}$$
$$h_t = o_t * tanh(c_t) \tag{11}$$

a) Block diagram of the proposed approach

b) LSTM cell (Kim et al., 1997).

Figure 4. Block diagram of the proposed approach and LSTM cell

Below is the time series consisting of Bist30 daily closing values between the years 2006-2018 in Figure 5. This data set contains data for 3020

business days. The data set used for the training of the model used in the study was colored in red and the data set used for the test was colored in green.

Figure 5. Training and test dataset

Four different verification studies were carried out for the proposed method.

4.1. Deep Learning Based Regression Model

The proposed regression model is used as a technical indicator. In line with the "Buy" and "Sell" signals obtained from the indicator, an investment was made in the BIST30 index with a fixed investment and at the end of the test period, the earnings status was compared with the MA indicator.

4.2. Error Rate

The difference between the proposed method and the actual prices was obtained with MSE. The equation "12" shows the real value of the y_t index, and y_p represents the estimated value (Fauzi., 2019).

$$MSE = \sum (y_t - y_p)^2 \qquad (12)$$

4.3. Metric Performances

By creating a confusion matrix on the test data for the proposed method, performance metrics were obtained based on the predictions obtained for the next day of the index (Up/Down).

Tablo 2. Confusion matrix

Predicted trend		True trend	
		Up	Down
	Up	tp	fn
	Down	fp	tn

The metric values that can be obtained on this contrast matrix are shown between "13-16". *Acc* gives the overall accuracy rate. *Precision* and *Precision* are important in the interpretation of misclassifications. F_1 can interpret *Precision* and *Recall* metrics together (Visa et al., 2011).

$$Acc = (tp + tn)/n \qquad (13)$$
$$Precision = tp/(tp + fp) \qquad (14)$$
$$Recall = tp/(tp + fn) \qquad (15)$$
$$F_1 = \frac{2 * Precision * Recall}{(Precision + Recall)} \qquad (16)$$

The tp, tn, fn and fp values used in the contrast matrix were obtained with a hybrid approach by using the regression model developed and the real values of the index. TP, TN, FP and FN values were obtained according to the rules in "17-20" order.

$$tp = tp + 1 \; if \; (y_t > y_{t-1} \; and \; (y_p > y_{p-1} \; or \; y_p > y_{t-1})) \qquad (17)$$
$$tn = tn + 1 \; if \; (y_t < y_{t-1} \; and \; (y_p < y_{p-1} \; or \; y_p < y_{t-1})) \qquad (18)$$
$$fp = fp + 1 \; if \; (y_t < y_{t-1} \; and \; (y_p > y_{p-1} \; or \; y_p > y_{t-1})) \qquad (19)$$
$$fn = fn + 1 \; if \; (y_t > y_{t-1} \; and \; (y_p < y_{p-1} \; or \; y_p < y_{t-1})) \qquad (20)$$

4.4. Algorithmic Trading

Algorithmic trading buy/sell transactions were performed: In general, one of the purposes of algorithmic transactions is based on earning by staying in the index direction. In this context, instead of using the "Buy" "Sell" signals of the model given for the first purpose, buy and sell transactions based on direction prediction were performed for the next day of the index. In other words, if an increase is foreseen for the next day, BIST30 shares were estimated with fixed investment and the portfolio was held until the next day the decrease was predicted. When the decrease was predicted, the portfolio was sold at the current value of the index. The threshold value

for the index increase has not been determined and commissions in the purchase and sale transactions have been ignored.

5. Experimental Results

As discussed in the proposed method section, four different scenarios were designed for the study and verification studies were carried out.
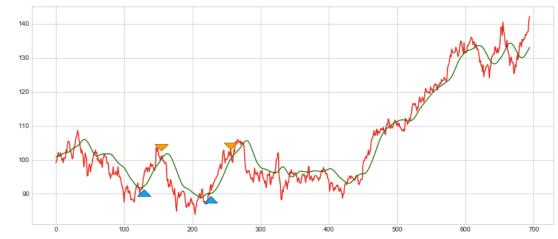
5.1. Regression Model

The buy/sell signals developed with the approach suggested in Figure 6 are given. In the figure, buy signals are given in dark blue and sell signals in orange. The line chart in red is the actual value of the index, and the line chart in green is the regression curve used for buy/sell. As in other indicators, buy / sell signals are used at the intersection of the regression curve, which is used as the real price and prediction in the period between t and $t-1$. If the real price goes up by cutting this regression curve upwards, "Buy" is generated, if it goes down to the bottom by cutting downwards, a "Sell" signal is generated. In the profit/loss simulation study, when the "Buy" signal was received with fixed investment, the BIST30 index was invested with the instantaneous value of the portfolio, and when the "Sell" signal was received, the sale was made at the instant price of the index. The results are given comparatively in Table 3. At the end of the time obtained with the test data, the portfolio value increased by 24.6%, compared with the 9-days SMA, the results are quite close to each other, but better results were obtained when the 50-days SMA reference was taken. In the period when the volatility is high in the financial markets, it is not desirable to have a long portfolio period. In this context, the average waiting time is shorter than the other two methods with the proposed approach.

Table 3. Profit simulation based on regression indicator

Number	Regression indicator		9 days SMA		50 days SMA	
	Profit/Loss	Portfolio period (days)	Profit/Loss	Portfolio period (days)	Profit/Loss	Portfolio period (days)
1	-0.97	1	-0.97	1	-0.97	1
2	-2.19	1	-2.19	1	-2.19	1
3	-0.48	5	-0.480	5	-0.48	5
4	-1.03	7	-1.49	9	-1.03	7
5	-2.42	3	-1.72	1	-2.60	33
6	8.19	39	8.00	33	6.10	51
7	-0.49	9	-2.514	7	**-6.13**	3
8	**10.9**	35	**11.33**	53	-0.86	1
9	1.82	13	-2.47	7	-4.04	1
10	-2.47	7	-2.98	9	-0.84	7
11	-2.18	11	**-4.04**	1	-1.67	3
12	**-4.04**	1	-0.75	5	**30.83**	171
13	-0.75	5	-1.78	15	-1.13	1
14	-0.38	1	10.52	39	-0.48	1
15	-1.78	15	-0.61	3	-2.74	11
16	9.08	3	8.20	43	6.918	7
17	-0.54	5	-0.12	5		
18	5.78	27	3.54	25		
19	-0.53	1	-0.93	13		
20	-0.28	3	0.15	21		
21	-0.20	1	5.67	7		
22	-0.51	1				
23	3.54	25				
24	0.10	7				
25	-0.41	1				
26	2.27	19				
27	-2.81	1				
28	6.91	6				
	Regression indicator		**9 days SMA**		**50 days SMA**	
Most profits per transaction	10.9		11.33		30.83	
Most loss per transaction	-4.04		-4.04		-6.13	
Avarage days	9.03		14.4		19	
Total transactions	28		21		16	
Number of transactions resulting in profit	8		7		3	
Number of transactions resulting in loss	20		14		13	
Portfolio profit	**%24.69**		**%24.7**		**%14.84**	

a) Examples of Buy / Sell signal obtained with the proposed approach

b) Proposed approach and 9 days SMA

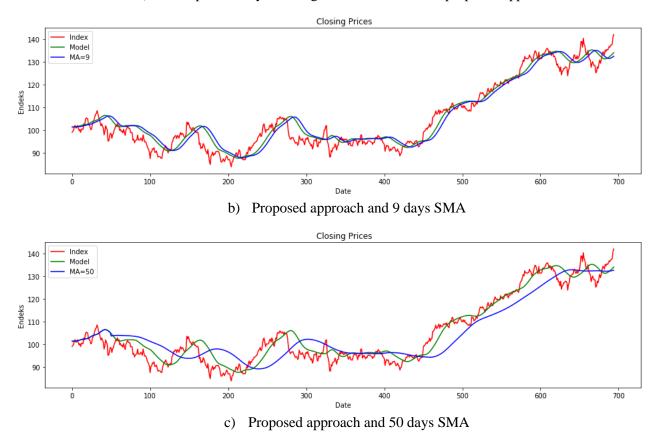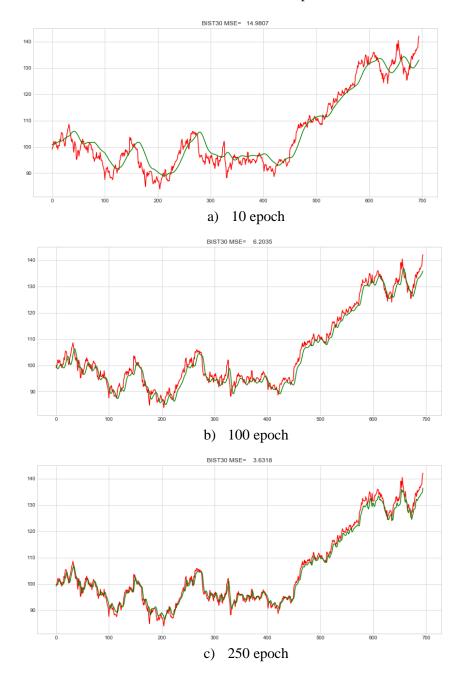c) Proposed approach and 50 days SMA

Figure 6. Examples of Buy/Sell signal obtained with the proposed approach, 9 days SMA and 50 days SMA

When the comparative results given in Table 3 are interpreted on the chart, the approach suggested in Figure 5.b is quite close to the 9-days SMA, and the profit obtained with the test data is very close to each other. When the 50-days SMA is compared with the approach suggested in Figure 8.c; After the 110th day, the "Buy" signal was captured earlier with the proposed method, for this process the "Sell" signal was captured earlier compared to the 50-day moving average. A similar situation is valid for transactions realized after 220 days. Both the "Buy" and "Sell" signal were caught earlier than the 50-day average. Both transactions yielded more profit and less waiting

time compared to the 50-day moving average. However, after the 500th day, the 50-day moving average caught an earlier "Buy" signal, the "Sell" signal for this transaction was obtained earlier with the proposed approach, but less profit could be obtained. This situation coincides with real-life technical analysis processes. Technical analysts and portfolio managers never invest in a single indicator. As a result, satisfactory results were obtained with profit / loss simulation in the study.

5.2. MSE Error

The second verification method performed is the comparison of the difference between the deep learning regression model and the real values with the MSE error rate. Below, MSE error values obtained with models with different number of epochs developed for price prediction are given in Figure t. The lowest MSE value was obtained when the system trained 500 epoch. In addition, when the system tilted 5000 epoch, the MSE value decreased from 2.6 to 2.4. In studies such as

image classification, the MSE value is desired to be close to 0, but the MSE value obtained due to the volatility in the time series in financial forecast applications is satisfactory. In another similar study for Dow 30 shares, MSE values ranging from 0.4 to 562 were obtained for 30 stocks (Fauzi., 2019). Development environment 2.7 Ghz i5 is a computer with 8 GB Ram configuration. Experimental studies were carried out using Python programming language and pandas, numpy, keras libraries. On this computer 5.000 epoch takes about 5 hours.
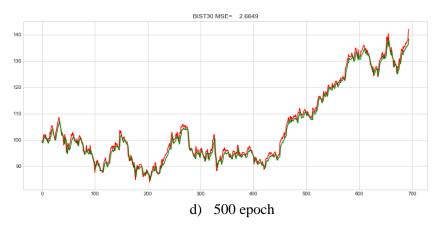
a) 10 epoch

b) 100 epoch

c) 250 epoch

d) 500 epoch

Figure 7. MSE values obtained with the developed approach

5.3. Metric Performances

The confusion matrix obtained according to the number of training rounds in Table 4 below are

obtained using the values obtained with the index closing and regression model of 694 working days. In this context, the highest accuracy was obtained when the system trained 100 epochs.

Table 4. Confusion matrix and portfolio profit

Confusion matrix	10 epoch		100 epoch		500 epoch	
	Up	Down	Up	Down	Up	Down
Up	340	20	324	36	312	48
Down	83	251	53	281	73	261
Total transactions	144		170		115	
Accuracy	0.85		0.87		0.82	
Precision	0.8		0.85		0.81	
Recall	0.94		0.9		0.86	
F_1	0.86		0.87		0.83	
Portfolio profit	%12		%9		**%39**	

5.4. Algorithmic Trading

The last experimental study is an algorithmic process simulation based on the index direction predictions given above. The proposed approach is to invest when an increase is estimated in the index and to sell the portfolio when a decrease is predicted. The best profit was achieved with 39% when the system trained 500 epoch. This value is higher than 24% profit from the first verification method. However, the number of transactions increased as expected. Despite 28 buy/sell transactions, 115 transactions have been realized with an algorithmic trading approach. No linear correlation was found between earnings ratio and Acc and other performance metrics. However, this is not a generalizable finding. The biggest reason for this is the volatility on time series. When the system was trained for 500 rounds, accuracy fell from 87% to 82%, but the portfolio profit increased to 39%.

6. Conclusions and Future Works

In this study, an experimental study was carried out for the financial estimation by using the data of BIST30 2006-2018 range. A regression model based on deep learning was developed using the BIST30 index daily closing data. The 2015-2018 range of the data was used for testing. The developed approach has been confirmed by four different experimental studies. In the first, the values estimated by the regression model were used as a technical indicator. When the technical indicator approach obtained was compared with the moving average used in the literature, a very approximate result was obtained when the period was selected for 9 days. When the period was selected as 50 days, higher profit was obtained with the proposed approach. The second verification method is to obtain the MSE value based on the difference between the real value of the index and the predicted values. MSE value was obtained as 2.4 in the study. In most machine learning applications, MSE can be obtained under 1 and close to 0. However, the MSE value

obtained due to excessive volatility in the time series in the financial forecast transaction is satisfactory. The third approach is to estimate the direction of the index using the regression model. This study was confirmed by creating a contrast matrix. The final verification study is an algorithmic transaction gain simulation based on the buy / sell transaction while remaining in the index direction. In this scenario, it gained 39% value in the portfolio with 82% correct direction prediction.

In the study, 50-60 day history values of the index were used for regression output in the 4-layer LSTM model. In the future, a hybrid approach based on Q-learning is planned to be developed using technical indicator data, global economic data, candlestick chart types and trend formation patterns. This study is an introduction to comparison and interpretation for these and other studies in the future. With future studies, accuracy, error and gain simulation studies will be carried out by using short, medium and long term test data on stock and sector basis.

Acknowledgement

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