O 110. STOCK PRICE FORECASTING WITH A FINANCIAL RATIO BASED NEURAL NETWORK ALGORITHM

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ABSTRACT: Forecasting stock prices is quite difficult due to uncertainty, chaotic nature and noise in financial markets. The aggregated impact of factors such as political instabilities, financial fragility, international financial integrity, technological developments and change in investor risk preferences make the estimation of stock prices harder. However, the challenge of developing a good estimation model in such an environment, the positive contribution of a successful model to the return of investment make the problem attractive for researchers. It is known that machine learning algorithms are useful in generating predictions in such chaotic environments as stock market, which have multiple sources of data flow. In this study, three stocks traded in Borsa İstanbul are selected according to different criteria and price estimation performances of proposed artificial neural network model together with known support vector machines, logistic regression, random forest and naive bayes classifier machine learning algorithms are compared. 18 financial ratios frequently used in evaluation of company performances with 102 other independent variables are used as inputs and monthly rate of return of stocks in 2009-2018 period are classified and estimated. Analyses on given period have shown that the proposed artificial neural network algorithm is a classifier that can be used as an alternative to other algorithms for stock market forecasting

Keywords: Artificial neural networks, logistics regression, naive bayes classifier, random forest, stock price forecasting, support vector machines

1. INTRODUCTION

Stock markets have grown by 320% since 2009 and reached a size of $ 80 trillion. (Edwards, 2017). However, despite increasing interest, forecasting trends in stock prices for profit is a challenging task due to complexities like rapid changes in economy, the subjective views of investors and political alterations. Stock exchanges are one of the economic environments most open to rapid changes caused by random fluctuations.

Stock market time series are generally dynamic, non-parametric, chaotic and noisy. For this reason, there are researchers who think that stock market price movements are a random process with fluctuations seen more clearly in short-term windows. (Khaidem, 2016) However, some stocks generally tend to develop linear trends over long-term time windows. In any case, there is a need to accurately predict trends in stock prices in order to maximize capital gains and minimize losses.

The importance of valid stock price prediction model applications have increased as a result of developments in financial forecasting modeling and increasing computer capabilities; with these models short term earning expectations increased compared to long-term expectations ("Means, Ends and Dividends", 2012). Nowadays, it is believed that 90% of the daily volume in stock markets is generated by investors using technical analysis, and most of this volume is generated with the help of prediction models developed by computer based algorithms (Cheng, 2017). Therefore, the quality of the forecasting model is directly related to the earnings in the stock market.

The application of machine learning models in stock market behavior is a relatively new phenomenon. This approach differs from traditional prediction and diffusion modeling methods. Pioneer models used in computerized stock forecasting included statistical methods such as time series model and multivariate analysis (Gencay, 1999; Timmermann and Granger, 2004; Bao and Yang, 2008). In these initial models, stock price movement was evaluated as a function of time series and solved as a regression problem and the success of the problem results were determined by comparing the actual value of the stock at that period. However, estimating the exact values of the stock price is quite difficult due to its chaotic structure and high volatility. As a matter of fact, studies that evaluate stock value estimation as a classification problem instead of a regression problem become more widespread. In this context, the main purpose of the recent studies is to design an intelligent model that predicts future trends in the movement of stock price with the information obtained from market data by using machine learning techniques. As in this study, the predictive outputs in general models aim to support the decision-making processes in stock exchange investments.

Within the scope of this study, an artificial neural network algorithm (ANN) which also uses financial ratio input variables in addition to the studies in the literature is proposed in order to estimate the direction of change for monthly prices of selected stocks traded on Borsa İstanbul (BIST) between March 2009 and December 2018. The results of the proposed algorithm were compared with the prediction results of Support Vector Machines (DVM), Logistic Regression Algorithm (LR), Naive Bayes Classifier Algorithm (NBS) and Random Forest Algorithm (RO) which are frequently used in estimation models and better results are obtained.

2. MATERIALS AND METHODS

2.1. Algorithms

The results of the proposed algorithm were compared with four algorithms frequently used in the literature.

2.1.1. Logistic Regression Algorithm

Logistic Regression is a multi class classification algorithm. In order to make multiple classifications, one vs all approach is used, by giving each cluster of data once marked as correct to the algorithm all groups are separated. The decision is always made according to the value of the hypothesis function in the range [0,1]. In order to separate decision groups, the data is divided into groups with a polynomial function called decision boundary. The sigmoid (logistic) function can be used to obtain results within the specified range and to assign the results to decision groups, as in ANN. Then a cost function that is convex and can give minimum cost value is sought. As in linear regression, in logistic regression, it is tried to reach the minimum point that makes the derivative value zero from the starting point taken with the parameters determined using gradient descent methods.

2.1.2. Support Vector Machines

DVM tries to divide data groups into optimal hyperplanes to maximize generalization capability. It identifies the data close to the hyperplane from the data groups as a support vector, and excludes other data, and only works on these training data groups. If data groups cannot be separated linearly, decomposition is achieved by increasing the data size with a generated polynomial.

Since the new N-dimensional space increases the computational load, the kernel function is applied to establish a relationship between the previous space and the new space. Kernel function has varieties as sigmoid kernel, radial kernel and polynomial kernel. Function parameters are found with the help of k-fold cross validation method.

2.1.3. Naive Bayes Classifier

NBS, which is used in classification problems, is one of the easiest data mining algorithms that can be applied to big data sets as fast as possible. It is a classification technique developed on Bayes' Theorem. NBS, which is called naive because it assumes even closely correlated predictive variables as independent, can yield better results than many sophisticated classification models.

Bayes' Theorem states that the conditional probability of the B event occurring with the occurrence of the A event can be calculated from the inverse conditional probability and the marginal occurrence probability of the A-B events.

$$P(A|\mathrm{B}) = \frac{P(A) * P(B|\mathrm{A})}{\mathrm{P(B)}} \tag{2.1}$$

Bayes Rule for two conditional events

Assuming that the number of events is more than two and the events are mutually independent, the probability sum of k A_j events covering the entire event space is 1 and the formula in the following equation applies:

$$P(A_i|\mathrm{B}) = \frac{P(A_i) * P(B|A_i)}{\sum_{j=1}^{k} P(A_j) * \mathrm{P}(\mathrm{B}|A_j)} \qquad (2.2)$$

Bayes Rule for multi conditional events

Therefore, by using a frequency table and probability table, when it is desired to classify a new observation, it can be classified by Bayes' theorem considering the probability values of the training set data (Cichosz, 2015).

2.1.4. Random Forest Algorithm

Random forest is one of the methods of supervised machine learning. It can be used in a regression environment as well as in a classification environment. It is a tree based method. Tree-based methods essentially group the data set by "if-then" propositions and divide the predicted observation space into zones. In case of regression the sum of square errors; in case of classification the wrong classification rate is being minimized.

One advantage of the decision tree configuration is that it can be determined which prediction variable is more decisive on the dependent variable. As we move up on the decision trees, the effect of the variables on the results increases. These algorithms are preferred because of their simple and easy to understand structure.

General structure of random forest algorithm to be used for comparison is:

For each T_b, b = 1… $b_{max.}$:

Step 1: Control of the number of observations in the end nodes, if the number of observations in all end nodes has reached the specified minimum number of observations go to Step 5.

Step 2: Randomly select m from the total p variable,

Step 3: Select the variable that makes the best separation in the training set from the selected m variable,

Step 4: Split end node into two sub-nodes, return to Step 1

Step 5: Save tree as T_b, stop if the maximum number of branches has been reached, if not return to Step 1. (Amrehn et al., 2018)

2.1.5. Proposed ANN Algorithm

In this study, multilayer perceptron (MLP) which is one of ANN algorithms is used. MLP is the most known and most commonly used type of neural network. In most cases, in the MLP algorithm, signals are transmitted in one direction from the input neuron to the output neuron within the network. This type of ANN architecture is called feedforward architecture. Figure 2.1 shows a feed forward MLP architecture.

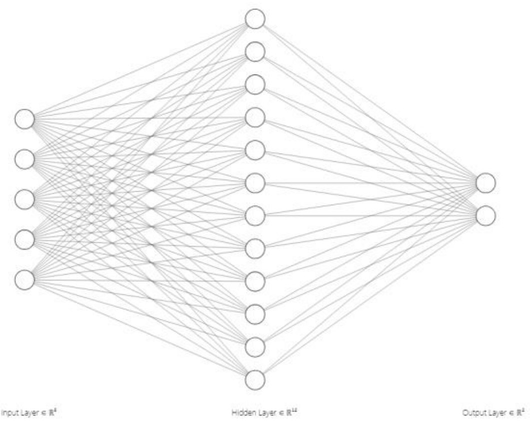

Figure 2.1. Multilayer Perceptron Architecture

As shown in Figure 2.1, MLP has a layered structure. While the data from the outside world enters the system from the input layer, the output layer shows the result that the algorithm finds for the relevant data. Non-multilayered structures can only separate the solution space linearly (McCulloch and Pitts, 1943). The layer(s) which has no relation with the outside world, processes the data it receives from the input neurons and obtains a result value and transmits this result to the next layers is the hidden layer.
Communication between neurons refers to the ignition of the neuron. A neuron processes the weighted values it receives from the precursor neurons bound to it, and transmits it by weighting all of the neurons to which it is linked in the next layer if a threshold is exceeded. Basically, Machine learning means that the algorithm that gives the wrong result can reach the correct result with small changes made in this weight and threshold values.
In order for small changes in weight and threshold values to affect the algorithm results proportionally with the change, neurons should not only take values in binary system (0,1), but also be able to take and ignite intermediate values. In this sense, the most commonly used neuron structure is a sigmoid neuron, a type of neuron that can show slight changes in parameters and always take value in the range [0,1].

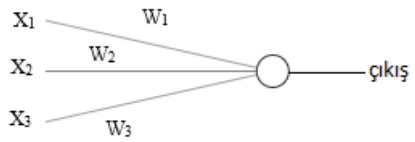

Figure 2.2. Structure of Sigmoid Neuron

As shown in Figure 3.4 and used in the study, the activation function output value of a single sigmoid neuron that takes x_1, x_2, x_3… input values by weights w_1, w_2, w_3… and with a threshold value of b is:

$$\frac{1}{1+ e^{(-\sum w_j * x_j - b)}} \tag{2.3}$$

Sigmoid activation function
In order to evaluate the performance of the algorithm, a cost function is required which will assign zero to the correct estimated observations, assign cost to the wrong estimated observations, and depend on the weight and neuron firing thresholds (bias). If training data set input values are x, and the desired output value is y(x) vector (For instance, if output 3 is correct in grouped in a 4 output system, y (x) must be $(0,0,1,0)^T$) matrix of algorithm weights is w, ignition thresholds is vector b, training set total number of observations is n, algorithm outputs for each observation is vector α then the cost function is:

$$C(w,b) = \frac{1}{2n}\sum_x \| y(x) - a \|^2 \tag{2.4}$$

Cost Function
Thus, the cost function is mean squared error.
The cost reduction process, which is the determination of the most appropriate weight and threshold values for the algorithm, is performed by the gradient reduction method. In this method, cost function is changed step by step in derivative direction for each variable to reach global minimum. Gradient vector in two-variable system is:

$$\nabla C \equiv \left(\frac{\partial C}{\partial v_1}, \frac{\partial C}{\partial v_2}\right)^T \tag{2.5}$$

Gradient Vector
Effect of changes in variables on gradient vector is:

$$\Delta v = -\eta \nabla C \tag{2.6}$$

Gradient-variable relationship
The value of η -mostly in the range of (0,1)- which determines the speed at which the problem approaches to its minimum point and is called the learning rate. The gradient reduction method aims to minimize the cost function mean square error and the reduction is continued until a certain number of

iterations on the training set called epoch is reached (Egeli ve ark., 2003). Epoch limit of 2000 was used in the study.

2.2. Determination of Data Set

Studies on the estimation of financial data have generally focused on the estimation of stock market index values on a daily or monthly basis (Taran et al., 2015).

In daily forecasting studies, daily input data such as exchange rate, technical analysis indicator values, historical stock data and index values of other stock exchanges are used as input variables. Since macroeconomic indicators and company financial reports are announced in longer periods such as monthly and quarterly, the forecasting models in the studies that use the relevant variables mostly consist of monthly periods. This study was carried out on monthly basis because the financial ratios used from the quarterly financial statements as 66 of the total 120 variables used in the study are being published for monthly or longer periods. Taking into account the presence of historical data, data quality and the structural break created by the 2008 financial crisis in the data time series, 118 monthly data were used between March 2009 and December 2018.

2.3. Data Resources

Interest rates, survey data, money supply information and macro variables gathered from Central Bank of the Republic of Turkey (CBRT) Electronic Data Delivery System; inflation rates from Turkish Statistical Institute (TurkStat); stock market indexes and commodity prices from investing.com website; historical stock values and technical analysis indicator data from yahoo finance website; company financial ratios from Finnet Financial Analysis Program.

2.4. Determination of Company Shares

Within the scope of the study, Garanti Bank Joint Stock Company (JSC) Class A Share (GARAN), Petkim Petrokimya Holding JSC Class A Share (PETKM) and Turkish Airlines JSC Class A Share (THYAO) stock values are used in the estimations.

While determining the shares used in the study, five considerations made: stock liquidity, early stock listing in stock market, sector differences, volatility differences and the behavior (trend) differences. Month-end values of the related shares in the working period are as in Figure 2.3.

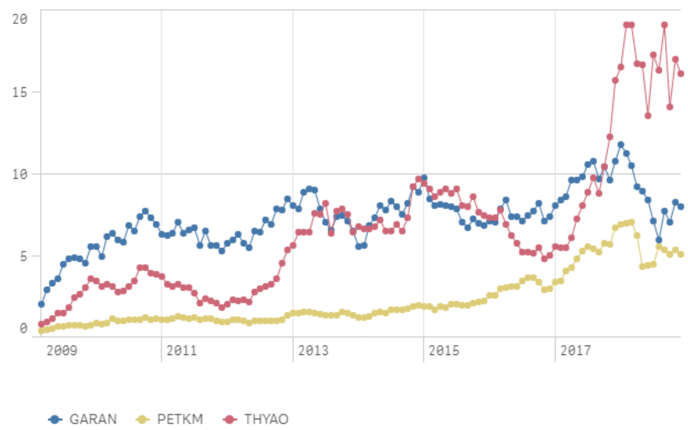

Figure 2.3. 2009-2018 Stock Month-End Closing Values

2.5. Financial Ratios Used

The financial ratios used as variables are obtained from the ratios used in the sectoral balance sheet evaluation ratios within the scope of the CBRT Sectoral Balance Sheets studies (CBRT, 2017) and from the ratios frequently used by investors using the relevant company balance sheets and income statements. Some financial ratios could not be used for GARAN because of the balance sheet differences between financial companies and real sector firms and they can not be calculated. 18 financial ratios used in the study are given in Table 2.1.

Table 2.1. Financial Ratios Used

Current Ratio	Current Assets / Current Liabilities
Acid Test Ratio ?	(Cash + Marketable Securities + Accounts Receivable) / Current Liabilities
Cash Ratio	Cash and Cash Equivalents / Current Liabilities
Inventory Turnover	Sales / Average Inventory
Accounts Receivable Turnover	Net Credit Sales / Average Accounts Receivable
Asset Turnover Ratio	Total Sales / (Beginning Assets + Ending Assets) / 2
Leverage Ratio	Total Liabilities / Total Assets
Short Term Liabilities Ratio	Short Term Liabilities / Total Liabilities
Long Term Liabilities Ratio	Long Term Liabilities / Total Liabilities
Shareholder's Equity Ratio	Shareholder's Equity / Total Assets
Debt to Equity Ratio	Total Liabilities / Total Shareholders' Equity
Asset Return Ratio	EBITDA / Total Assets
Earnings per Share	Net Profit / Common Shares Outstanding
Operating Profit Margin	Operating Income / Sales Revenue
Income Ratio	Net Income / Current Assets
Price Earnings Ratio	Market Value per Share / Earnings per Share
Book to Market Ratio	Common Shareholders' Equity / Market Cap
Price to Sales Ratio	Market Value per Share / Sales per Share

2.6. Other Variables Used in Algorithm

Input variables other than financial ratios were used in the study. Table 2.2 summarizes types and numbers of variables are used.

Table 2.2. Variable Groups

Variable Type	Explanation	#
Share Variables	Values ??depending on the share, changing with share value	4
Technical Analysis Variables	Moving averages commonly used by investors	5
Index Variables	BIST 100 and some major market index values	24
Currency & Commodity Price Variables	Parity and gold price values	18
BIST Detailed Variables	BIST sub-index value and return values	10
Macro Variables	Money supply, reserve, budget values ??and national survey results	36
Inflation Variables	Overall and narrowed comprehensive inflation indicators	5
TOTAL		**102**

2.7. Data Preparation

1. Monthly - (if not quarterly) data for 120 variables and estimated 3 stock values were obtained from June 2008 to December 2018.
2. Simple moving average (SMA) and Simple Exponential Smoothing (SES) forecasts were calculated over the closing prices for 2-3-6 months.
3. 9 variables based on share value (Opening GAP, volatility, distance to floor, distance to ceiling, 2-3-6 months SMAs and 2-6 months SESs) and 18 variables (6 for GARAN) depending on company financial statements were kept separately for each company and combined with the other 93 variables were common for each company.
4. The missing data of 21 variables (12 for GARAN) whose data are available in quarterly periods were completed by linear interpolation method.
5. The percentage changes of all independent variables and dependent variable end-of-month closing value for the estimated month have been calculated.

$$Changing\ value\ at\ time\ t = \frac{Value\ at\ time\ t - Value\ at\ time\ (t-1)}{Value\ at\ time\ (\mathrm{t}-1)} \qquad (2.7)$$

Percentage conversion of variable values

6. Since the estimations are made for the next month share values, the independent variable values of period t-1 and the dependent variable value of period t were matched.
7. All the share value closing price change dependent variables were sorted from small to large and the number of observations is divided into two equal groups.

8. 5-fold cross validation (5-fold cross validation) was applied to separate learning and test data and min-max normalization was applied to each of the dependent variables in the learning group and their values were adjusted to [0-1] range.

2.8. Evaluation Criteria

Confusion matrix was used as the evaluation criterion within the scope of the study (Kohavi ve Provost, 1998).

Table 2.3. 2 - group classification confusion matrix

		Forecasted Value	
		Group 1	Group 2
Real Value	Group 1	$X_{1,1}$	$X_{2,1}$
	Group 2	$X_{1,2}$	$X_{2,2}$

In the confusion matrix given in Table 2.3, the gray areas show that the predicted value is the actual value, in other words the percentage of observations correctly. Therefore accuracy is:

$$Accuracy = \frac{X_{1,1}+X_{2,2}}{\text{Total \# of Observations}} * 100 \qquad (2.8)$$

Group estimated accuracy (%)

Since the estimation values and actual values were distributed equally to the groups, no detailed evaluation criteria were needed (Kubat et al., 1998).

2.9. Software and Solution Environment

Microsoft Excel 2016 was used for creating raw data set and data editing. The solution of the proposed algorithm is made by using deep learning toolbox in MATLAB program (Version 7.1). The compared algorithms were solved in WEKA program (Version 3).

3. RESEARCH FINDINGS

The closing price percentage changes for 118 months between March 2009 and December 2018 were classified for each of the three stocks by sorting and grouping according to the number of observations as shown in Table 4.1. For example, PETKM's monthly change was the most negative with -30.96% to -2.39% and its 59-month value was chosen as Group 1 of that stock and the rest as Group 2.

Table 3.1. Closing Price Change Data Grouping and Value Ranges

	Group 1		Group 2	
	Min	Max	Min	Max
PETKM	-30,96%	1,65%	1,67%	31,77%
THYAO	-26,40%	1,56%	1,58%	34,02%
GARAN	-16,32%	0,14%	0,18%	42,57%
# of Observation	59		59	

The ANN algorithm was tested with different parameter values and data preparation methods without suggesting, and the ANN model which gave the best results in experiments was chosen to be proposed in the study. Parameters and methods were tried in experiment models are given in Table 4.2.

Table 3.2. ANN Parameter Values & Methods

Parameter Value & Method	Experimented Value	Proposed Value
# of Hidden Layer	1, 2	1
# of Neuron in Hidden Layer	6, 8, 10, 12, 16	12
Momentum Constant	0.1, 0.2, 0.3	0.2
Learning Rate	0.15, 0.2, 0.3, 0.4	0.3
Activation Function	Sigmoid, RELU	Sigmoid
Normalization Method	Min-Max, Z-Score	Min-Max
Epoch	2000	2000
Cross Validation	5	5
# of Iterations	10	10

The general structure of the proposed ANN is given in Figure 3.1. Other algorithms are calculated with the default parameter values in the WEKA program.

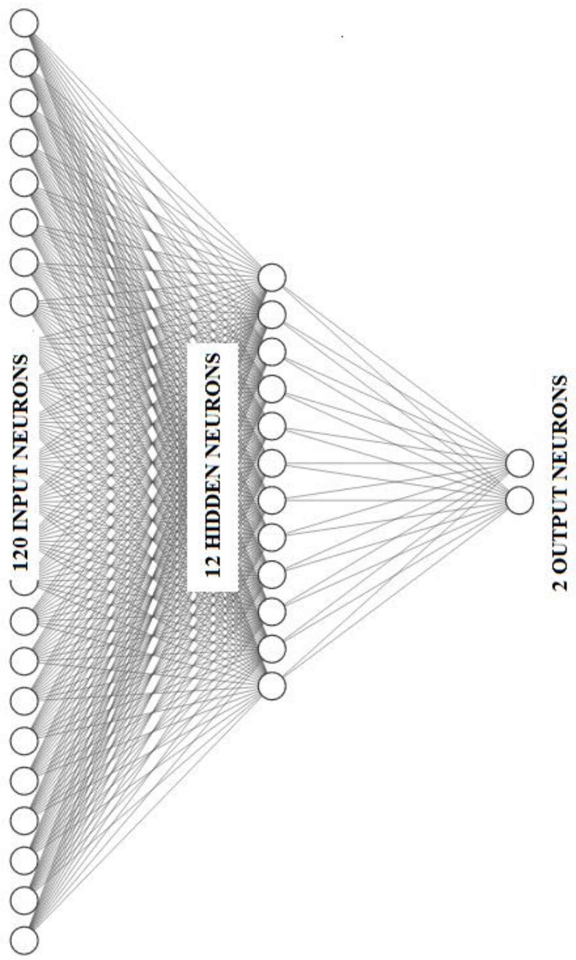

Figure 3.1. Recommended Algorithm Architecture

Table 3.3. General Results

GARAN		Forecasted Value									
		ANN		NB		LR		RF		SVM	
		Group 1	Group 2	Group 1	Group 2	Group 1	Group 2	Group 1	Group 2	Group 1	Group 2
Real Value	Group 1	77,97%	25,42%	57,63%	38,98%	66,10%	33,90%	72,88%	20,34%	67,80%	30,51%
	Group 2	22,03%	74,58%	42,37%	61,02%	33,90%	66,10%	27,12%	79,66%	32,20%	69,49%
Accuracy		76,28%		59,33%		66,10%		76,27%		68,65%	
Performance		1		5		4		2		3	
THYAO		Forecasted Value									
		ANN		NB		LR		RF		SVM	
		Group 1	Group 2	Group 1	Group 2	Group 1	Group 2	Group 1	Group 2	Group 1	Group 2
Real Value	Group 1	74,58%	25,42%	64,41%	37,29%	64,41%	16,95%	67,80%	25,42%	67,80%	30,51%
	Group 2	25,42%	74,58%	35,59%	62,71%	35,59%	83,05%	32,20%	74,58%	32,20%	69,49%
Accuracy		74,58%		63,56%		73,73%		71,19%		68,65%	
Performance		1		5		2		3		4	
PETKM		Forecasted Value									
		ANN		NB		LR		RF		SVM	
		Group 1	Group 2	Group 1	Group 2	Group 1	Group 2	Group 1	Group 2	Group 1	Group 2
Real Value	Group 1	77,97%	25,42%	59,32%	37,29%	72,88%	25,42%	61,02%	30,51%	66,10%	30,51%
	Group 2	22,03%	74,58%	40,68%	62,71%	27,12%	74,58%	38,98%	69,49%	33,90%	69,49%
Accuracy		76,28%		61,02%		73,73%		65,26%		67,80%	
Performance		1		5		2		4		3	

As a result, in the study conducted on 118 observations in the period of 2009 March - 2018 December; ANN made the best grouping for all three stocks. In 10 iterations, 76.28% of GARAN with the average of 90 observations; 74.58% of THYAO with the average of 88 observations; 76.28% of PETKM with the average of 90 observations were correctly classified.

4. RESULTS AND DISCUSSION

In this study, t time stock value change percentage estimation was made by using t-1 time variable values. The closing price change rates of three different stocks traded in BIST in March 2009 - December 2018 were tested using a model of 120 variables including financial ratios on 5 different machine learning algorithms. ANN has yielded the best results for all three stocks. It is concluded that ANN is a good alternative to the other algorithms in estimation of stock value change.

In the scope of the study, to prevent the possibility of overfitting to keep the number of input variables of the ANN around the number of observations, longer-term lagged variable values were not used (Liu et al., 2017). In future studies, feature selection methods can be used to reduce the number of independent variables and to use variable values such as t-2 and t-3. In addition, studies on stocks in developed markets, stocks of companies in different sectors or stock market index values can be carried out.

Unlike this study, other methods such as hyperbolic tangent and rectified linear units can be tried as activation function when ANN algorithm is established. There was no need to reduce the number of variables because there was no possibility of excessive overfitting, but methods such as Principle Component Analysis or regularization can be used on the variables and studies with different variables can be carried out in future studies.

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