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MODELLING AND PREDICTING STOCK RETURNS IN ISTANBUL STOCK EXCHANGE (ISE): AN ARTIFICIAL NEURAL NETWORK APPROACH

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ABSTRACT

Prediction models and techniques are of great ability and importance to all economic agents. More specifically, successful prediction of stock exchange rates and returns are beneficial for investors who want to make higher returns as well as governments in decision-making. Therefore, this study examines the predictive capability of a backward propagation artificial neural network. Moreover, it is aimed at determining whether a backward propagation neural network is capable of accurately predicting the Borsa Istanbul (BIST 100 index) stock returns. Interest rates, inflation rates, exchange rate, money supply, industrial production index of the Turkish economy as well as five world stock market indices are used as input variables to predict returns. The experimental results suggest that the model successfully predicts the monthly return of the BIST 100 index with over 95% accuracy rate. This implies that artificial neural networks provide a promising substitute for stock market predictions for economists and practitioners.

Keywords: Stock returns, Artificial Neural Networks, Istanbul Stock Exchange, Predicting.

1. INTRODUCTION

Predicting the stock exchange market returns has been accepted as one of the most attractive topics in the world of academic economists since it is difficult to determine the fluctuations in prices on the stock exchange. Due to the high levels of market volatility of the stock exchange markets, examining the reaction of stock prices and investing in the stock market carries higher risk as compared to other sectors. Prediction models and techniques are of capability and great importance to all economic agents. More especially successful prediction of stock prices and returns are beneficial for investors who want to make higher returns as well as governments in decision-making. This study examines the predictive capability of a backward propagation artificial neural network.

The global economy has and is largely affected by the movements on the stock market, therefore the need to analyze stock markets indices with not just domestic factors but also the factors of the major exchanges around the world they interact with. Both external and internal factors influence the value of stocks that are traded on the exchange. Internal factors include the estimated earnings of the company as well as changes in the financial structure of the company. Macroeconomic factors such as exchange rates, interest rates, gold prices and GDP as factors external to the firm. Studies on the prediction of BIST 100 index mostly focus on the interaction between the BIST 100 index and various macroeconomic variables with methodologies ranging limited to statistical estimation techniques and time series models (Kabaklari, 2014; Yildiz 2014).

Neural networks are similar to the biological structure of neurons processing elements of the human brain. The popularity regarding the use of the artificial neural network in the prediction of the BIST 100 index has gained momentum in recent times (Aygoren, Saritas & Morali, 2012; Yakut, Elmas & Yavuz, 2014). In this study, instead of the conventional macroeconomic variables used to predict BIST 100 in most studies, our dataset is on advanced international stock market indices and a few key domestic factors used as an input variable (independent variables) to predict the stock returns of the BIST 100 index using the Artificial neural network method. However, this study is limited in the fact that "insider trading" in Turkey, natural disasters, political uncertainty and wars directly affect the movement of the BIST 100 index, thus making prediction quite difficult.

The rest of the paper is organized as follows: section 2 discusses some related works in the prediction of stock market indices, section 3 we explore the neural network method used in this study as well as the dataset used, and finally, section 4 discusses the results and conclusions.

2. EMPIRICAL LITERATURE

In the recent finance literature, various machine-learning algorithms are being applied to predict stock market movements as well as returns. Due to the non-linearities that characterize financial time series, Artificial Neural Networks (ANN) (Di Persio & Honchar, 2016; Vui, Soon, On, Alfred & Anthony, 2013) and Support Vector machines (SVM) (Markovic, Stojanovic, Stankovic and M. Bozic, 2014; Sapankevych and Sankar, 2009) have been used (Atsalakis and Valavanis, 2009).

In a study by (Martinez, Da Hora, João, Meira and Pappa, 2009), the daily minimum and maximum stock prices were predicted using Multi Layer Perceptron (MPL). In a bid to decide which technical indicators are the most important indicators for prediction, all the technical indicators were used as inputs for the network and then MLP classification algorithm was used. (Kayal, 2010) also employed MPL to forecast the foreign exchange market by utilizing the most basic technical indicators like moving averages and several time lagged standard deviations which is compared with random selection.

A study on the Shangai Stock Market index by (Guo, Wang, Yang and Miller, 2015) used the Radial Basis Function Neural Network (RBFNN) to train different technical variables of the stock market in order to predict Shangai Stock Market index for the next day. Moreover, to reduce the data feature set dimension, Principal Component Analysis (PCA) was employed. (Markovic, Stojanovic, Stankovic and M. Bozic, 2014) however, predicted the trend of Belgrade stock exchange index (BELEX15) using the Support Vector Machines with feature selection. Several other studies have used other classifiers such as Decision trees (DT) (Basti, Kuzey and Delen, 2015), Logistic Regression (LR) (Dutta, Bandopadhyay and Sengupta, 2012), Naive Bayes (NB) (Gunduz and Cataltepe, 2015) and Random Forest (RF) (Ballings, Van Den Poel, Hespeels and Gryp, 2015) on indices and stock prices of various stock markets.

Studies on Borsa Istanbul (BIST 100) generally use historical index prices and technical indicators in most recent times. (Bildirici and Ersin, 2009) applied a combination of Autoregressive models and Artificial Neural Networks (ANN) to predict the daily returns of the BIST 100 index. (Boyacioglu and Avci, 2010) used the Adaptive Neuro Fuzzy Inference System (ANFIS) for the prediction of the BIST 100 index. A study that combined Artificial Neural Networks (ANN) and Supports Vector Machines (SVM) as classifiers predicted the direction of the BIST 100 index using technical indicators as inputs concluded that the performance of both classifiers is remarkable in the prediction process (Kara, Acar Boyacioglu and Baykan, 2011).

Gunduz and Cataltepe (2015) made use of the Naive Bayes (NB) algorithm for the prediction of the direction of daily BIST 100 index. Their study proposed the analysis of news articles by using a feature selection method called Balanced Mutual Information (BMI) to predict future market movements.

Pehlivanlı, Aşıkgil, and Gülay, (2016) to predict next day price, indicators that were deemed irrelevant and redundant were removed from the dataset by combining filter-based feature selection methods, training SMV classifier and finally applying the voting scheme. Subsequently, as a way of simulation of these processes, technical and macroeconomic indicators as well as a real dataset from Borsa Istanbul, were used. The results indicated that prediction performance improves as a result of the feature selection methods applied.

Peng and Jiang (2016) predicted the direction of stock movements using Deep Neural Networks. The study used both news and price data for its network. The Deep neural network had 1024 hidden layer used in the classification. The study found significant improvement in prediction performance when features from news articles are added to price features.

Turkmen and Cemgil (2015) used stacked-autoencoders (SAE), an unsupervised deep learning structure to investigate the direction of share prices traded on the NASDAQ Stock Exchange. The inputs for the deep learning model were the technical indicators calculated from price data. The evaluation of model performance by accuracy and F-measure metrics concludes that the Stacked-Autoencoders (SAE) model gave the best performance with SMV method.

Chen, Zhou and Dai (2015) deployed long-short-term memory (LSTM) network to predict China's Stock returns. The study used two dimensional data points with 30-days-long sequences with 10 features obtained from China's Stock market historical data. Also, the 3-day earning rate was used as class labels for data points. The results showed that Long Short-Term Memory (LSTM) improved classification performance compared to random prediction models.

3. DATA AND METHODOLOGY

The ANN model, which was developed by mimicking the working structure of the human brain, consists of a total of three layers: the input layer where historical data is entered, the output layer from which the outputs are obtained, and the hidden layer between the input-output layers. This model, which has been used frequently for the prediction of financial crises in recent years, produces highly successful estimates in explaining nonlinear relations (Tetik, Karahan & Solak, 2015; Kartal, 2019). In this paper, the neural network prediction method use was the Multilayer Neural Network (MLNN) due to its popularity in artificial neural network (ANN) models. The MLNN model structure is given in figure 1 below.

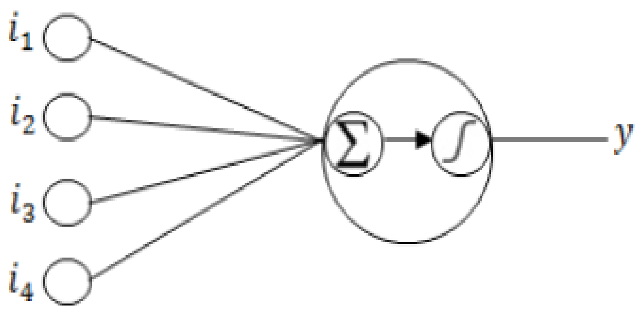

Figure 1. Structure of Neurons in A Multilayer Neural Network

From figure 1, the MLNN model has four inputs (i_1, i_2, i_3, i_4) and one output ***y***. In this model, the neurons go through two processing units. Thus, linear and nonlinear units. In the linear unit, each input is multiplied by the separate weight values (w_1, w_2, w_3, w_4) and then summed. Next, the results from the linear unit are sent to the nonlinear unit for other nonlinear processes. Operations in the linear unit are given by equation 1 below:

$$n = \sum_m i_m w_m \qquad (1)$$

In the nonlinear unit, the resulting sums from equation 1 pass through an activation function (sigmoid function, hyperbolic tangent function and step function) to obtain a result, which is then sent to the output of the neuron. Output y is estimated as shown in equation 2 below:

$$y_{output} = f(n) \qquad (2)$$

where f represents the selected activation function.

3.1. Model Accuracy

In Multilayer Neural Network (MLNN) models, the measurement of its accuracy is based on the Mean Squared Error (MSE). MSE is the average of the distance between each target variable and the estimated value in the linear unit. This MSE is therefore minimized based on the Root Mean Squared Error (RMSE). RMSE provides a means to determine the rate of error between predicted values and actual values being measured. The smaller the value of RMSE, the better. Hence, the closer RMSE is to zero, it implies increasing prediction capability of the neural network. Equations 3 and 4 show the Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) respectively.

$$MSE = \frac{1}{N}\sum_{i-1}^{N}(d_i - \bar{d}_i)^2 \qquad (3)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i-1}^{N}(d_i - \bar{d}_i)^2} \qquad (4)$$

3.2. Structure of Neural Network

The MLNN model used in this study to predict the market index of the Istanbul Stock Exchange is shown in figure 2. Our model consists of eleven input variables which include: interest rates, Inflation rates, Turkish Lira exchange rates to US dollar, Money supply, Industry production index of the Turkish economy, gold prices as well as five world stock market indices.

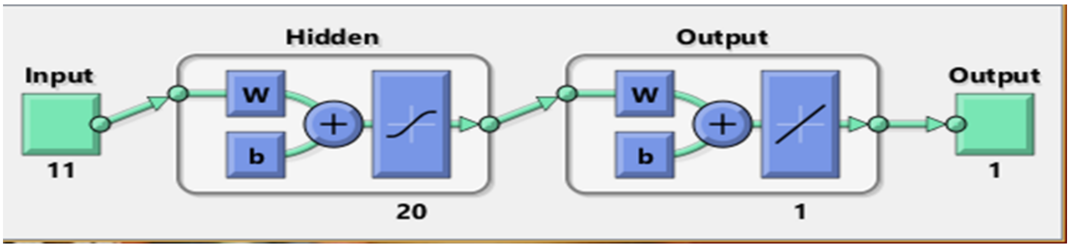

Figure 2. Multilayer Neural Network Used

From figure 2, 20 hidden neurons are used in the model. The sigmoid activation function was selected for processing in the nonlinear unit. This study adopted the Levenberg-Marquardt Back-Propagation algorithm for training the network. Among all kinds of training algorithms, Levenberg-Marquardt (LM) modified algorithms is the fastest. The analysis was carried out in RMATLAB 2018a.

3.3. Normality Test

The normality test for all the variables in this study was conducted with SPSS 23. Table 1 gives the summary results for the test for normality.

Table 1. Results of Normality Test

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
InterestRates	0.197	240	0.000	0.925	240	0.000
ConsumerPriceIndex	0.180	240	0.000	0.853	240	0.000
USDollarExchangeRate	0.206	240	0.000	0.810	240	0.000
M2forTurkey	0.252	240	0.000	0.728	240	0.000
ProductionofTotalIndustry	0.181	240	0.000	0.896	240	0.000
BİST100index	0.186	240	0.000	0.832	240	0.000
NASDAQ100index	0.090	240	0.000	0.909	240	0.000
NIKKEI225İndex	0.104	240	0.000	0.968	240	0.000
DAX30Index	0.111	240	0.000	0.946	240	0.000
ChinaStockMarket	0.148	240	0.000	0.882	240	0.000
BOVESPAIndex	0.198	240	0.000	0.837	240	0.000
Gold Prices	0.291	240	0.000	0.734	240	0.000

According to table 1, all variables significantly not normally distributed at 1% significance level. Thus, the null hypotheses for both the Kolmogorov-Smirnov and Shapiro-Wilk test of normality are rejected. This implies the variables of this study have non-normal distribution. Consequently, the spearman correlation matrix for all the variables was also computed to see how they influence the BIST 100. The results of the Spearman correlation are presented in table 2:

Table 2. Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1)Interest rate	1.000											
(2)Inflation rate	-0.589	1.000										
(3)Exchange rate	-0.388	0.889	1.000									
(4)Money Supply	-0.575	0.989	0.887	1.000								
(5)Industry index	-0.595	0.953	0.800	0.942	1.000							
(6)BİST 100	**-0.573**	**0.976**	**0.831**	**0.966**	**0.954**	**1.000**						
(7)NASDAQ 100	-0.147	0.736	0.587	0.729	0.724	**0.802**	1.000					
(8)NIKKEI 225	0.283	-0.746	-0.854	-0.737	-0.643	**-0.649**	-0.428	1.000				
(9) DAX 30	-0.193	0.760	0.579	0.753	0.771	**0.830**	0.942	-0.393	1.000			
(10)Chinese index	-0.370	0.845	0.743	0.837	0.815	**0.842**	0.785	-0.623	0.837	1.000		
(11)BOVESPA	-0.567	0.971	0.798	0.960	0.949	**0.982**	0.806	-0.631	0.838	0.860	1.000	
(12)Gold Prices	-0.873	0.581	0.347	0.566	0.580	**0.559**	0.106	-0.221	0.167	0.278	0.561	1.000

In this study we used the random selection cross-validation method was employed to test the Multilayer Neuralk Network model in order to prepare the dataset for the prediction of the BIST 100. In this method, the data is randomly distributed into training set; validation set; and testing set. In this study, the training dataset was 70% of the dataset, 15% for validation, and 15% for testing. To normalize the results, the same distribution ratios of the datasets were used on 10 different rearrangements of the datasets. Figure 3 shows the training, validation and test prediction accuracy of experiment 1 of the 10experiments used in our neural network training phase.

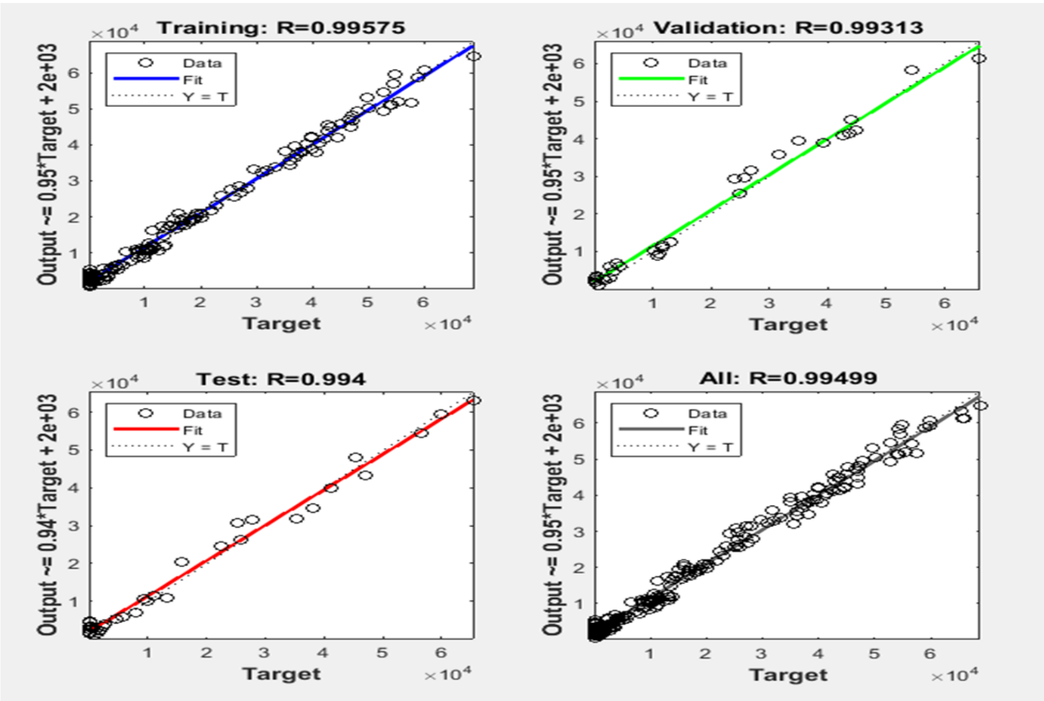

Figure 3. The Performance Graph of MLNN Training of the Experiment-1

Furthermore, the percentage of prediction accuracy, as well as the mean square error (MSE) values for experiment 1, are shown in figure 4.

Results

	Samples	MSE	R
Training:	168	4749348.98833e-0	9.95750e-1
Validation:	36	7105766.93942e-0	9.93131e-1
Testing:	36	6503577.30125e-0	9.94004e-1

Figure 4. The MSE Values and Accuracy Performance of MLNN Training from Experiment 1.

Table 3 summaries the performance accuracy of each of the 10 experiments conducted in this study as well as the Root Mean Square Errors (RMSE). The RMSE values are minimized to ensure error minimization. Therefore, the average of the prediction accuracy is indicative of the performance of our model in predicting the BIST 100 index.

Table 3. The Results of The RMSE Estimates

Experiment Number	Percentage of prediction accuracy	Root mean square error (RMSE)
1	99.40	2550.211
2	99.65	1488.126
3	99.23	2504.284
4	99.06	2361.800
5	99.69	1657.517
6.	93.76	7421.961
7	99.67	1477.302
8	98.80	2791.349
9	98.61	3508.003
10	98.80	2454.046
Average (Mean)	**98.67**	**2821.46**

From table 3, the results show that the Multi-Layer Neural Network model used in the prediction of the BIST 100 index has a prediction accuracy and Root Mean Square Error of 98.67% and 2821.46 respectively.

4. CONCLUSION

Prediction models and techniques come are important for organizations and individuals during decision making and investment periods. As it is the goal of every investor to achieve higher returns from their investments, predicting the stock market index with high accuracy is very important to help guide investors. In this study, instead of the conventional macroeconomic variables used to predict BIST 100 in most studies, our dataset is on advanced international stock market indices and a few key domestic factors used as an input variable (independent variables) to predict the stock returns of the BIST 100 index using the Artificial neural network method. Our model consists of eleven input variables which include: interest rates, Inflation rates, Turkish Lira exchange rates to US dollar, Money supply, Industry production index of the Turkish economy, gold prices as well as five world stock market indices. From the results from this study, we observe a strong relationship between the BIST 100 index and the market indices of the five international stock markets as seen in the correlation table 2. Moreover, the Multi-Layer Neural Network (MLNN) model used predicted the BIST 100 index with an accuracy of over 95%. However, future studies on predicting BIST 100 could be made more optimal by including indices developing countries domestic factors such as “insider trading” in Turkey, natural disasters, political uncertainty and financial literacy level due to their direct effect on the movement of the BIST 100 index.

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