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Random Regression Forest Model using Technical Analysis Variables: An application on Turkish Banking Sector in Borsa Istanbul (BIST)

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Abstract

The purpose of this study is to explore the importance and ranking of technical analysis variables in Turkish banking sector. Random Forest method is used for determining importance scores of inputs for eight banks in Borsa Istanbul. Then two predictive models utilizing Random Forest (RF) and Artificial Neural Networks (ANN) are built for predicting BIST-100 index and bank closing prices. Results of the models are compared by three metrics namely Mean Absolute Error (MAE), Mean Square Error (MSE), Median Absolute Error (MedAE). Findings show that moving average (MAV-100) is the most important variable for both BIST -100 index and bank closing prices. Therefore, investors should follow this technical indicator with respect to Turkish banks. In addition ANN shows better performance for all metrics.

Key Words: *Random Forest Regression, Artificial Neural Networks, Technical Analysis, Banking Sector, Variable Importance.*

JEL classification: *G13, G17*

Introduction

Uncertainty of stock prices is an essential problem for the investors. There are lots of factors in the market that increases the volatility of the prices, such as high capital movement (Wong et. al., 2003). Owing to these problems, estimating the prices of the stocks in the market becomes very difficult. As a result of this situation, investors are anxious about the changing prices of the stocks in the market. Because of this aspect, they need to analysis related to the prices of these investments.

There are two different methods that can satisfy these needs of the investors, which are fundamental analysis and technical analysis (Oberlechner, 2001). In fundamental analysis, economic conditions and financial ratios of the company are analyzed whereas in technical analysis approach, future price of the stock is tried to be estimated by analyzing past prices of this stock (Abarbanell and Bushee, 1997). According to the researchers that are in favor of technical analysis, historical price of a stock is significant. By using this data, the graph of the prices is created. Owing to this aspect, the trend of the stock can be defined. Because of this situation, it can be possible to predict future prices (Lo et. al., 2000).However, there are also some approaches in the literature that disagree the fundamental and technical analysis. Efficient market hypothesis, which was defined by Eugene Fama in 1970, is one example of these approaches. It refers that all available information in the market is reflected in the price of the stock (Fama, 1998). Therefore, it can be said that it is impossible to beat the market according to this hypothesis. In other words, if the market is efficient, investors cannot gain profit by using information obtained from the market. According to the efficient market hypothesis, only new information about the company can change prices (Malkiel, 1991). There are also 3 type of efficient market hypothesis (Jensen, 1978). With respect to weak form hypothesis, historical prices reflect prices at the moment (Poshakwale, 1996). Thus, it is not possible to predict future prices by using historical prices. Additionally, in semi strong form, in addition to the historical data, all published information related to the company is reflected in the prices (Groenewold and Kang, 1993). Hence, published information cannot also help to predict future prices. Moreover, in strong form hypothesis, all information is represented in the price. The secret information related to the company, which is not published, is not helpful to estimate future prices as well (Bray, 1981). On the other hand, according to the technical analysis approach, there are some assumptions. First of all, the stock price is affected by only its supply and demand (Neftci, 1991). Other factors, such as inflation and economic growth do not directly affect the stock prices. The main reason behind this situation is that supply and demand includes all kinds of these factors. Another assumption of technical analysis approach is that prices move in the direction of a trend for a long time (Mills, 1997).

Technical analysis is mostly used in order to define the future prices of the stocks. In addition to this issue, this approach is also popular in foreign exchange markets. There are many studies that try to estimate foreign currency by using technical analysis (Osler, 2003), (Neely et. al., 1997), (Taylor, 1994), (Change and Osler, 1999). Furthermore, there are also some studies that evaluates the effectiveness of central bank intervention by using technical analysis (Neely and Weller, 2001), (Saacke, 2002).

Many researchers are in favor of technical analysis approach. They claim that by just considering financial ratios of the company can be misleading. The main reason is that there can be many other important factors which are not stated in financial reports, such as quality of the management. On the other hand, technical analysis approach is also criticized by some analysts. They think that past prices of a stock do not always give the correct information about future prices (Stevens, 2002). Because of these issues, the studied related to the technical analysis is very significant. Hence, the aim of this study is to evaluate the efficiency of technical analysis.

The paper is organized as follows: second part describes technical analysis method. The third part provides information about random forest. The fourth part includes details of analysis. Finally a conclusion is presented.

Literature Review

Sen and Chaudhuri made a study about the prediction of a stock price by using time series data of this stock. Within this context, they used the time series of the index values of the Auto sector in India during 2010 to 2015. According to the technical analysis result, it was concluded that time series data is very helpful in order to predict the stock price (Sen and Chaudhuri, 2016). Cervelló-Royo and others tried to identify new stock market trading rule based on technical analysis. For this purpose, the data of 91,307 observations from the US Dow Jones index were used in this study. It was concluded that the European market is more inefficient than the US market (Cervelló-Royo et. al., 2015).

Urquhart and others made a study to understand whether technical analysis can beat the market or not. Within this scope, gold and silver market is used in this study. As a result of the analysis, it was determined that parameters that use longer histories are more successful than the others. Another result of this study is that intraday technical trading rules can be profitable in the gold market but not for the silver market (Urquhart et. al., 2015). Fernandes tried to identify the effect of stock characteristics on technical analysis profitability. Within this scope, the data of 38 stocks from Portuguese stock market and the PSI 20 index for the period between 2003 and 2013 was used. As a result, it was found that investing models, which are based on technical analysis, are not always profitable (Fernandes, 2015).

Bitvai and Cohn made a study to test whether price movements can be predicted from the past data. For this purpose, they created a linear model with the aim of profit maximization. As a result of the analysis, it was determined that market movement can be predicted by using technical analysis (Bitvai and Cohn, 2015). Shen and Tzeng tried to create a model for technical analysis in order to be helpful for investment decision. In order to achieve this objective, the data of Taiwan Stock Exchange for the years between 2002 and 2014 was used in this study. They concluded that several technical indicators can be used together so as to provide better results (Shen and Tzeng, 2015). Wafi and others compared the performance of fundamental and technical analysis. Pooled cross sectional and time series analysis was used in this study in order to achieve this objective. Moreover, within this scope, the data of 37 nonfinancial companies listed in the Egyptian Financial Markets for the period between 1998 and 2009 was used. As a result of the analysis, it was determined that technical analysis method gives better results than fundamental analysis (Wafi et. al, 2015). Waworuntu and Suryanto tried to integrate fundamental and technical analysis in their study. So as to achieve this objective, the data of 183 firms from Indonesian Stock Exchange for the period between 2004 and 2009 was used. As a result of regression analysis, it was defined that using fundamental and technical analysis together provided better results (Waworuntu and Suryanto, 2015). Hoffmann and Shefrin tried to evaluate the performance of technical analysis in their study. In order to achieve this objective, they made survey with a sample of Dutch discount brokerage clients for the period between 2000 and 2006. According to this analysis, it was defined that investors using technical analysis have lower returns. Another important result of this study is that male investors use technical analysis more than female investors (Hoffmann and Shefrin, 2014).

Ko and others evaluated the performance of the technical analysis in Taiwan stock market. In this study, they created a new trading strategy by considering moving average signals. As a result of the analysis, it was determined that new trading strategy based on moving average signals provided successful results (Ko et. al., 2014). Vasileou examined the success of technical analysis in order to decide buy or sell the stock. For this purpose, he used simple moving averages rules in Greek stock exchange in this study. In addition to this situation, the data for the years between 2002 and 2012 was used. In conclusion, it was identified that using technical analysis provides better results (Vasileou, 2014). Rosillo and others made a study about the performance of technical analysis indicators. Within this context, Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), Momentum and Stochastic indicators were used for Spanish companies. It was concluded that the performance of technical analysis depends on the type of the companies (Rosillo et. al., 2013). Metghalchi and others tried to analyze the profitability of technical analysis approach. Within this context, they used the data of 9 popular technical indicators in Taiwanese Stock Market. In addition to this situation, they established 66 models in this study in order to achieve the objective. In conclusion, it was defined that there is a negative relationship between the number of technical indicator combinations and profitability (Metghalchi et. al., 2013). Amujamed and others made a study about the performance of technical methods used by investors in Kuwait Stock Exchange. Within this context, they prepared a survey to investors, technical analysts and investment analysts in Kuwait. As a result of the analysis, it was determined that technical analysis is the most credible approach for investors (Amujamed et. al., 2013).

Aldin and others tried to evaluate the performance of technical indicators in order to predict stock price. For this purpose, the data of Tehran Exchange Price Index (TEPIX) was tested by artificial neural network.

According to the results of the analysis, it was determined that technical indicators are very successful in order to predict stock price (Aldin et. al., 2012). Taylor and Allen made a study about technical analysis in foreign exchange market. Within this context, they conducted a survey to foreign exchange dealers in London. As a result of survey analysis, it was determined that 90% of dealers use technical analysis in their works. Another result of this study is that dealers trust technical analysis result for short time period. However, they prefer fundamental analysis in the long term (Taylor and Allen, 1992). Blume and others tried to investigate the applicability of stock exchange volume for technical analysis. They concluded that the volume is very informative in order to define the value of stock exchange. Another conclusion of this study is that it was defined that investors, who use statistical information, are more successful than the others in their investments (Blume et. al., 1994). Lam tried to integrate fundamental and technical analysis for financial performance prediction. Within this scope, financial data of 364 S&P companies for the years between 1985 and 1995 was used. In addition to this situation, neural networks method was used in this study so as to achieve this objective. As a result of the analysis, it was determined that using fundamental and technical analysis gives better results (Lam, 2004). Chavarnakul and Enke made a study related to the performance of 2 technical indicators of technical analysis approach. Within this scope, they used generalized regression neural network method. Furthermore, S&P 500 index data was used in this study so as to achieve the purpose. In conclusion, it was defined that stock trading using the neural network showed better performance than the results of stock trading without neural network assistance (Chavarnakul and Enke, 2008).

Schulmeister evaluated the performance of technical analysis in his study. Within this scope, he analyzed the profitability of 2580 technical models. As a result of the analysis, it was identified that while using daily data, the success of technical analysis declined over the years. Another important point of this study is that it was determined that if 30-minutes-data is used, technical analysis is always successful (Schulmeister, 2009).

With respect to researches in the field, technical aspect of performance based studies could be increased by adopting innovative techniques using hybrid models.

Technical Analysis Method

Technical analysis considers historical prices of a stock in order to predict future price. Historical prices help to make graph of the prices of the stock over the years. By analyzing this graph, the trend of the prices can be determined. This trend gives information about the future price of the stock. According to this analysis, historical prices reflect every inside of outside factors about this stock. Because of these aspects, economic factors are not taken into the consideration in technical analysis (Murphy, 2012).

Dow Theory

Dow Theory is the oldest form of technical analysis. This theory was created by Charles Dow who was the founder of Dow Jones and Company and the first editor of The Wall Street Journal. According to this theory, the economy is moving according to some trends. Therefore, he aims to identify the trend and estimate the prices of the stocks (Brown et. al., 1998).

There are some assumptions regarding this theory. First of all, it is accepted that the stock prices represent all important changes in the market. Therefore, in order to estimate the future price, nothing other than past prices is necessary to consider. Another assumption of this theory is that there are 3 different trends in the market which are primary trends, secondary trends and minor trends. Primary trends take more than a year whereas secondary trends take about 1.5 month. Moreover, the time of minor trends can be up to 15 days (Glickstein and Wubbels, 1983).

Bear and Bull Market

Bear market refers to the market in which the prices of a stock have a decreasing trend (Cook, 1985). Due to this decreasing trend, it is thought that this stock will lose value. Therefore, investors are unwilling to buy this stock. This problem leads to decrease in the number of buyers and increase in the number of sellers in the market.

On the other hand, bull market means the market in which there is an increasing trend in the stock price (Ritter and Warr, 2002).Therefore, in this market prices are expected to increase in the future. Because of this expectation, investors are willing to buy this stock. On the other side, investors, who have this stock, do not want to sell this stock. When all these factors are taken into consideration, it can be concluded that bull market causes more buyers and less sellers.

The Difference between Technical Analysis and Fundamental Analysis

In fundamental analysis, financial performance of the companies and economic conditions are taken into the consideration (Thomsett, 2006). In other words, financial ratios provided from the balance sheet and income statements and economic factors such as economic growth and inflation rate are analyzed in this process. As a result of this analysis, the price of the stock is calculated. After that, a decision related to this stock is made by comparing market price and the calculated price.

On the other hand, in technical analysis approach, the past prices of the stocks were evaluated (Edwards et. al., 2012).That is to say, by analyzing previous price movements of the stocks, this approach tries to estimate the future price of this stock. Therefore, it can be said that in technical analysis method, economic conditions and financial ratios of the company are not evaluated. In technical analysis approach, price graphs of the stocks are analyzed.

Technical Analysis Variables Used in this Study

There are a lot of technical analysis indicators used in order to predict the future prices of the stock. Some of the most popular ones are explained in this study.

Accumulation and Distribution (A/D) Index: This index gives information whether the movement trend will go on or not by taking into the consideration of the changes in prices and volume. The reference point is accepted as “0”. If the value of the index is greater than this reference value, it gives a signal to buy. On the other hand, having a value less than the reference value is accepted as a selling signal (Kim, 2003).

The calculation of this index is given below.

$$\frac{[(\text{Closing Price} - \text{Min. Price}) - (\text{Max. Price} - \text{Closing Price})]}{(\text{Max. Price} - \text{Min. Price})} * \text{Volume}$$

Bollinger Bands (BB): This indicator was created by John Bollinger. Two different bands are identified about the prices of the stock. When the price of the stock reaches one of these bands, it means that the price will move to other direction. For example, if the prices increase and reach the band above, this means that there is a high probability of decreasing price. Therefore, this stock should be sold. Similar to this situation, decreasing price, which reached the below band, gives a signal to buy (Leung and Chong, 2003).

Commodity Channel Index (CCI): This index was created by Donald Lambert in 1980. It gets values between -100 and +100. If the price of the stock is greater than 100, this refers that the price is abnormally high. Therefore, it can be said that there is a high risk of price decreasing. Moreover, the situation in which the price is less than -100 shows that price is too low. This situation gives information that there is a high probability that prices may increase (Davies, 1995).

The formula of CCI is given below.

$$\text{CCI} = \frac{(\text{Middle Price} - \text{Moving Average of Middle Price})}{\text{Total}(\text{Middle Price} - \text{Moving Average of Middle Price})/\text{number of days}} * 0.015$$

In this equation, middle price = (highest price + lowest price + closing price) / 3

Chaikin Oscillator: This index analyzes the relationship between the price and volume of the stock. If this index is high, it means that investors buy this stock. Also, decreasing trend of this index demonstrates that investors are selling this stock. This index was produced by Mark Chaikin (Utthammajai and Leesutthipornchai, 2015).

The formula of Chaikin oscillator is explained below.

$$\mathrm{CO} = \frac{(\text{Closing Price} - \text{Min. Price}) - (\text{Max. Price} - \text{Closing Price})}{(\text{Max. Price} - \text{Min. Price})} * \text{Volume}$$

Envelope (ENV): By using moving average of the stock prices, 2 different curves are provided. The price of the stock is expected to be between these curves. This index is similar to Bollinger Bands. If the value decreases up to the lower band, then it is accepted as a selling signal. Similar to this situation, if this value reaches to higher band, then this stock should be bought (Neftci, 1991).

Moving Average Convergence Divergence (MACD): This index, which was created by Gerald Apel in 1979, is one of the most popular indicators. It refers to the difference of two different exponential moving averages. These averages are mostly provided for 12 and 26 days. By using this index, investors try to estimate the future price of the stock. If average for 12 days is greater than the average for 16 days, then MACD index will be positive. Similarly, for the opposite case, it will be negative. If MACD has a positive trend, this means that the stock should be bought. On the other hand, MACD with negative trend gives information about selling the stock (Boxer, 2014).

The equation of moving average convergence divergence is given below.

MACD = Exponential Moving Average (12 days) - Exponential Moving Average (26 days)

Mostly, the moving average of MACD for 9 days is used. This value means the trigger curve. If MACD curve reaches the triggered curve with an upward trend, this is accepted as a signal to buy. On the other side, the opposite situation gives information about selling (Galloppo, 2009).

Momentum (MOM): This index shows the percentage change of the prices for a given period. By evaluating velocity in price changes, the power and continuity of the trend can be determined. The reference point of the momentum is 100. If it has a decreasing trend above the reference point, then this stock should be sold. Similar to this situation, increasing trend below the reference point gives information about buying of this stock. In addition to these issues, an increasing trend that reaches reference point is accepted as a buying signal. Moreover, if there is a decreasing trend which touches the reference point, this stock should be sold (Taylor and Allen, 1992).

The calculation of the momentum is explained below.

$$\text{Momentum} = [\text{Closing Price(last day)} / \text{Closing Price(n days before)}] * 100$$

Moving Average: It is the average value of the stock for a given period. This value leads the investor about the future price of the stock. There are different types of moving average. Simple moving average is calculated as the ratio of all prices to the number of days. Furthermore, weighted moving average gives more importance to the last days in the period. In addition to them, exponential moving average also rates the last days higher, but it does not eliminate the first days in the calculation. Moreover, in triangular moving average, prices of the middle days have higher rates (Brock et. al., 1992).

On Balance Volume (OBV): This index evaluates the relationship between changes in the prices and the volume. If both volume and prices increase at the same time, this shows that this increasing trend will go on. On the other side, if prices increase while the volume decreases, increasing trend in the prices is expected to change after a short time (Tsang and Chong, 2009).

The formula of OBV is emphasized below.

$$\begin{aligned} \text{OBV(new)} &= \text{OBV(old)} + \text{volume}, && \text{if closing prices (today)} > \textit{closing prices} \text{ (yesterday)} \\ &= \text{OBV(old)} - \text{volume}, && \text{if closing prices (today)} < \textit{closing prices} \text{ (yesterday)} \\ &= \text{OBV(old)}, && \text{if closing prices (today)} = \text{closing prices (yesterday)} \end{aligned}$$

Price Oscillator (POSC): This index compares two different moving averages like MACD index. One of these averages is for short time while other average is related to longer time. In addition to them, there is also a reference point between them. The fact that the band between two curves increases is accepted as a buy or sell signal. If the below chart reaches to the reference point, then the stock should be bought. On the other hand, if the above chart decreased to the reference point, this situation gives a signal to sell (de Castro and Sichman, 2007).

The equation of price oscillator is given below.

$$\mathrm{POSC} = \frac{[\text{Exponential Moving Average (12 days)} - \text{Exponential Moving Average (26 days)}]}{\text{Exponential Moving Average (26 days)}} * 100$$

Price Rate of Change (PROC): It shows the percentage change of the last day price with respect to a given date. If the last day price increases, it is accepted as a signal of buying. On the other side, the fact that this percentage goes down gives information about selling the stock (Kim, 2003).

The equation of this indicator is given below.

$$\mathrm{PROC} = \frac{[\text{Closing Price (today)} - \text{Closing Price (n days before)}]}{\text{Closing Price (n days before)}} * 100$$

It can be easily understood from this equation, there is a positive relationship between the prices and PROC value. 100 is accepted as a reference point. If PROC is less than this reference point and has a decreasing trend, this means that prices will go down. On the other hand, the value, which is more than 100 and has an upward trend, refers that the prices will decrease.

Relative Strength Index (RSI): This index evaluates the days in which prices increase or decrease by comparing the day before. There are two different reference points in this index which are 30 and 70. If the value is less than 30, it is accepted as a selling signal. Similar to this situation, being the value more than 70 gives information about buying. Also, between these two points, the trend of the index is significant in order to make buy or sell decision (Chong and Ng, 2008).

The equation of relative strength index is shown below.

$$\mathrm{RSI} = 100 - \frac{100}{1 + \mathrm{RS}}$$

$$\mathrm{RS} = \text{Average Gain} / \text{Average Loss}$$

If the closing price of today is greater than the closing price of the day which we compare, this means that there is a gain. On the other hand, if the closing price of the day which we select is higher than the closing price at the moment, there will be loss (Menkhoff and Taylor, 2007).

Stochastic: This index is one of the most popular indicators. It is mostly used by traders for short term aims. It compares the last price of the stock with the price for a period. It takes the value between 0 and 100. For this index, the values of 20 and 80 are important. An increasing trend below 20 demonstrates a signal to buy for the investors. On the other hand, if there is a decreasing trend above 80, the stock should be sold (Vora, 2011).

There are 2 different curves in stochastic indicator, which are %K and %D. The formula of %K is given below.

$$\%\mathrm{K} = \frac{\text{Closing Price} - \text{Min. Price in the period}}{\text{Max. Price in the period} - \text{Min. Price in the period}}$$

Furthermore, %D means the moving average of %K. Therefore, if %K has an upward trend and reaches to %D, this is accepted as a buy signal. Parallel to this situation, downward trend of %K means selling signal if it reaches to %D (Kim, 2003).

Volume: This index shows how many times a stock is transferred. If there is an increasing trend with high volume, it is accepted as a signal to buy. Similar to this situation, a decreasing trend with high volume means that this stock should be sold. In addition to these aspects, if the volume starts to decrease while it is increasing, it is thought a possibility for the trend to change (Blume et. al., 1994).

Williams %R (WLR): This index, which was created by Lary Williams, is the opposite of stochastic index. The term "%R" refers to the range. It means the difference between highest price and lowest price for a day. The value of this index can take part between 0 and -100. If there is an increasing trend below -80, this situation is accepted as a buy signal. Additionally, any decreasing trend stated below -20 gives information about selling (Bauer and Dahlquist, 1999).

$$\text{Williams \%R} = \frac{(\text{Max. Price} - \text{Closing Price})}{\text{Max. Price} - \text{Min. Price}} * (-100)$$

In this study, 8 of these indicators were used in order to assess the effectiveness of technical analysis. These indicators are explained in the table below.

Table 1: Variables used in the models

Variables	Explanation	Formula
Moving Average	It is the average value of the stock for a given period.	Total values of each day / The number of the days
Stochastic	It compares the last price of the stock with the price for a period	%K= (Closing Price-Min. Price in the period)/(Max. Price in the period- Min. Price in the period) %D= moving average of %K
Volume	It shows how many times a stock is transferred	-
Commodity Channel Index	It measures the current price level relative to an average price for a given period.	CCI=((Middle Price-Moving Average of Middle Price))/(Total(Middle Price-Moving Average of Middle Price)/number of days)*0.015
Moving Average Convergence Divergence	It refers to the difference of two different (for 12 and 26 days) exponential moving averages.	MACD = Exponential Moving Average (12 days) - Exponential Moving Average (26 days) Trigger = The moving average of MACD for 9 days
Momentum	It shows the percentage change of the prices for a given period.	Momentum = [Closing Price(last day) / Closing Price(n days before)]*100
Relative Strength Index	It evaluates the days in which prices increase or decrease by comparing the day before	RSI=100-100/(1+RS) RS=Average Gain / Average Loss
Williams %R	It means the difference between highest price and lowest price for a day.	Williams %R=((Max. Price-Closing Price))/(Max. Price-Min. Price)*(-100)

Source: Authors

Research and Methodolody

Random Forest

Making decisions by considering ideas of multiple people or experts (voice of crowd) has been a common practice in civilization and democracy. Similarly, a way of making prediction models more reliable is to combine the output of several different models. This approach is generally referred to as ensemble learning. Ensemble models often increase prediction performance over a single model by reducing the models' variance (Witten & Frank, 2011). They are general techniques that can be employed for classification and regression tasks. Today, ensemble learning has many real-world applications, including object detection and tracking, scene segmentation and analysis, image recognition, information retrieval, bioinformatics, data mining (Zhang & Ma, 2012). In recent years, ensemble models also have been applied in business and finance domains.

Ensemble models combine a series of t learned models (base models) namely $T_1, T_2, \dots . T_t$ for creating an improved composite global model T^*. A given data set (D) is used for creating t training set $(D_1, D_2, \dots D_t)$ where D_i is used to generate model T_i. Given an input (X), each model produces an output. For classification, the ensemble returns a class prediction based on the votes of the models or average of the outputs for regression tasks (Han et al., 2011). Steps needed to build an ensemble model can be expressed algorithmically as:

1. *for i=1 to t do*
2. *Create a training set* D_i *from* D.
3. *Build a model* T_i *from* D_i.
4. *end for*
5. *for each record* $x \in Test\ Set$
6. $T^*(x) = Aggreate\big(T_1(x), T_2(x), \ldots T_t(x)\big)$
7. *end for*

The most basic condition for an ensemble predictive model, to perform better than a single model predictive model, is that base models should be independent of each other. The advantage of aggregating several methods tends to be greatest if the methods are unrelated (independent). The advantage of aggregation disappears if the methods are identical (i.e., strongly correlated) (Ledolter, 2013).

Random Forest, introduced by Breiman (2001), is a general term for ensemble methods using decision trees as base models. It can process very large data sets, provides an estimate of variables' importance, has robust method for handling missing data, has a built-in mechanism for balancing unbalanced data sets and runs fast (Nisbet et al., 2009).

In literature, Random Forest is utilized in various financial applications such as: exploring financial soundness of companies (Kalsyte & Verikas, 2013), customer relationship management (Larivière & Van den Poel, 2005; Benoit & Van den Poel, 2012; Xie et al., 2009; Burez & Van den Poel, 2009; Coussement & Van den Poel, 2009), credit risk assessment (Marqués et al., 2012, (Florez-Lopez & Ramon-Jeronimo, 2015, Kruppa et al., 2013), novelty detection (Zhou et al., 2015), predicting stock index movement (Patel et al., 2015), developing seasonal stock trading model (Booth et al., 2014), predicting future performance of companies (Kalsyte et al., 2013).

Random Forest uses a large number of distinct, unpruned decision trees that are built by randomizing the split at each node of the decision tree. Each tree is likely to be less accurate compared to the tree built with the exact splits. However, by combining of these "approximate" trees in an ensemble it is often possible obtaining an improved model (Rokach & Maimon, 2008). Steps of random forest algorithm are presented in Figure 1.

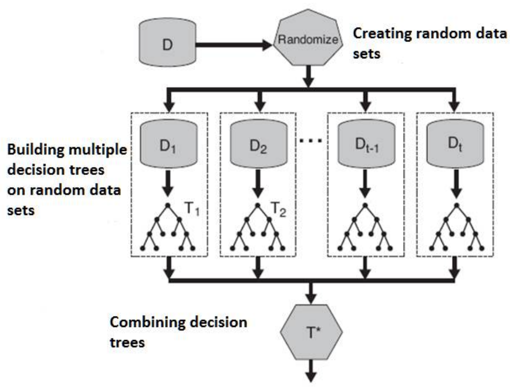

Figure 1: *Steps of Random Forest (Source: Tan et. al, 2006)*

Single decision trees suffers from high variance (after splitting a data set randomly into two halves and fitting decision trees on these data sets, it is possible to obtain two decision trees that are quite different). This makes decision trees unstable models. They are sensitive to minor perturbations in the training set. Random Forest uses a general-purpose method called bagging to stabilize decision trees. Bagging (*bootstrap aggregating*) is a technique that repeatedly samples with replacement (some observations may appear several times in the same data set while some may not be included). Each bootstrap sample has the same size as the original data set. On average, a bootstrap sample D_i contains approximately 63% of the original data. Each time a different data set is provided to decision trees so resulting models will usually be diverse satisfying one of the conditions needed for ensemble methods to work (Berthold et al., 2010; Malhotra & Jain, 2011). Observations, which are not present in the training set, are called Out of Bag (*OOB*) subset. A different *OOB* subset is formed for every individual tree. These subsets are used for evaluating the performance of individual trees (Rodriguez et al., 2012). The proportion between misclassifications and the total number of *OOB* elements gives an unbiased estimation of generalization error. The generalization error converges as the number of the trees increases so overfitting does not occur (Rodriguez-Galiano, et al. 2011).

If each decision tree is built by considering the exact same set of attributes, all the individual trees are likely to use very similar sets of attributes (perhaps in a different order or with different split values). This produces trees overly correlated with each other. If a tree tends to make mistakes in a region in feature space, then all the trees are likely to make mistakes in this region too, weakening opportunity for correction (Zumel & Mount, 2014). Random Forest algorithm tries to de-correlate the decision trees by randomizing the set of features that each tree is allowed to use. For each node m attributes out of all M possible attributes are selected at random and independently then best split conditions are determined by using Gini impurity measue on the selected m attributes. The optimal size of the subset of predictor variables is given by $\log_2 M+1$ (StatSoft, 2013). The randomness of attribute selection leads to robustness to noise and the attributes that have weak relationships with the target variable, to outliers, and to small changes in the training data set (Ledolter, 2013). Also, by controlling the number of attributes used for a split, the computational complexity of the algorithm is reduced. Finally, the trees in the random forest are not pruned, further making it light from a computational perspective (Gislason et al., 2006).

To quantify importance of a given variable, Random Forest uses the mean error (misclassification rate for classification models and mean square error for regression models) changes of trees in the forest when the observed values of the given variable are randomly permuted in the OOB samples (Genuer et al., 2010). $errOOB_t$ denotes the error of a single tree (t) on the OOB_t sample. To compute the importance score a given variable (X^j) values of (X^j) are randomly permuted in OOB_t. By this way, a perturbed sample ($\widetilde{OOB}_t^j$) is obtained. Denoting error of the tree on this perturbed sample as $err\widetilde{OOB}_t^j$ and the number of trees in forest as $ntree$, variable importance of X^j can be expressed as:

$$Variable\ Importance\ (X^j) = \frac{1}{ntree}\sum_{t=1}^{ntree}\left(err\widetilde{OOB}_t^j - errOOB_t\right)$$

An Application on Turkish Banking Sector in Borsa Istanbul (BIST)

The study includes 8 banks and 10 selected technical variables between 2010 and 2015. During model construction 2010-2013 period is used for training, 2014 and 2015 for testing. Firstly random forest models are constructed for predicting BIST -100 index and bank closing prices according to specifications. By using constructed Random Forest models variable importance score of each input is calculated. Then ANN models are built to compare the results of Random Forest. Analysis results of study is given in details below.

Table 2 shows the specifications that are used for building the Random Forest models. Number of the predictors are limited to 4 in accordance with the formula obtained the optimum predictor number. All random forest models consist of 100 decision trees as a default if stopping conditions are not met.

Table 2: Random Forest Specifications

Random Forest Options	
Number of predictors	4
Number of trees	100
Stopping Parameters	
Minimum *n* of cases	37
Minimum *n* in child node	5
Maximum *n* of levels	10
Maximum *n* of nodes	100
Advanced Stopping Conditions	
Cycles to calculate mean error	10
Percentage decrease in training error	5

Figure 2 presents the training and testing error for predicting XU-100 index. It demonstrates the basic mechanism of how the Random Forest algorithm can avoid overfitting. Generally, as more and more decision trees are added to the model, the error for training data (from which the respective decision trees are estimated) decreases. The same tendency should be observed for test error over the testing data. However, as more and more trees are added, test error starts to increase at one point while training error keeps decreasing. Commonly, this point is judged as the the evidence for beginning of overfitting. Ensemble models like Random Forest exploit overfitting problem as can be seen from Figure 2.

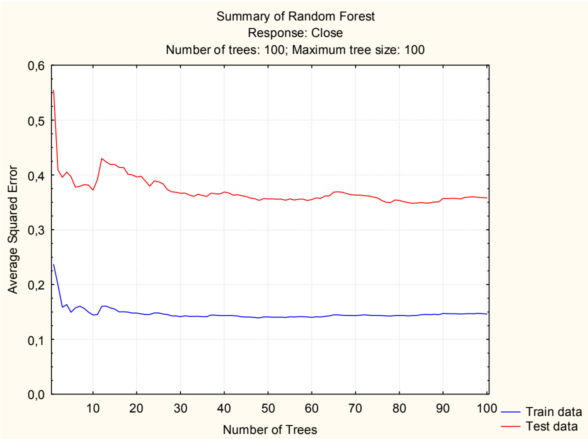

Figure 2: Training and Testing Error (XU-100 Index)

Importance scores of variables for both banks and XU-100 index are given in Table 3. According to the results, the number of variable having a score greater than 0.2 is 8 for Bank 1. This is the highest number among the banks. The average importance scores and ranking for all variables are computed. Accordingly, MAV(100) is the most important technical variable for all banks. TRIGGER(9), MACD(26,12), RSI(14) and VOL are placed in a consecutive order. For the model predicting XU-100 index, the most important variable is MAV(100). Ranking results are almost same with the average importance scores of banks. As expected, moving average with 100 days has the greatest effect in building prediction models for closing prices.

Table 3: The Importance Scores of Variables for Banks and Index

	B1	B2	B3	B4	B5	B6	B7	B8	Average	Rank (Banks)	XU-100	Rank (XU-100)
%D(3)	0,210	0,118	0,142	0,108	0,122	0,062	0,105	0,128	0,124	9	0,075	10
%K(5,3)	0,158	0,096	0,128	0,098	0,121	0,063	0,104	0,128	0,112	10	0,083	8
CCI(14)	0,204	0,119	0,147	0,112	0,131	0,070	0,109	0,159	0,131	8	0,078	9
MACD (26,12)	0,358	0,173	0,351	0,235	0,312	0,146	0,274	0,311	0,270	3	0,174	3
MAV(100)	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1	1	1
MOM(12)	0,227	0,141	0,149	0,104	0,147	0,080	0,143	0,194	0,148	6	0,112	5
RSI(14)	0,312	0,222	0,199	0,175	0,210	0,076	0,175	0,210	0,197	4	0,12	4
TRIG(9)	0,396	0,227	0,396	0,297	0,365	0,165	0,309	0,309	0,308	2	0,196	2
VOL	0,188	0,136	0,225	0,302	0,186	0,211	0,143	0,134	0,191	5	0,102	6
WLR(14)	0,201	0,125	0,156	0,103	0,150	0,065	0,125	0,162	0,136	7	0,086	7

To construct the optimal ANN models, a grid search considering different activation functions for hidden and output layers, number of hidden units are performed. As the error function sum of squares is utilized. Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm is employed for optimizing network weights. ANN model summaries can be seen in Table 4. B4 and B8 are the most complex ANN models among others having 12 and 11 hidden layer units respectively. The most frequently used activation function in both hidden and output layers is exponential function.

Table 4: ANN model summaries

	Best Network Topology	**Hidden Activation Function**	**Output Activation Function**
XU-100	10-4-1	Tanh	Logistic
B1	10-4-1	Tanh	Logistic
B2	10-4-1	Exponential	Exponential
B3	10-5-1	Exponential	Exponential
B4	10-12-1	Exponential	Tanh
B5	10-5-1	Exponential	Exponential
B6	10-4-1	Exponential	Exponential
B7	10-5-1	Exponential	Exponential
B8	10-11-1	Tanh	Identity

Results for all models are summarized in Table 5 for XU-100 and banks. Mean Absolute Error (MAE), Mean Squared Error (MSE), Median Absolute Error (MedAE) are the metrics used for comparing Random Forest (RF) and Artificial Neural Networks (ANN) models. ANN presents the most successful results for all banks with respect to all metrics. Bank 6 has the lowest MAE and MSE values of 0,2748 and 0,1073 respectively while B2 has the lowest MedAE value of 0,2223.

Table 5: *Model Results for XU-100 Index and Banks*

		MAE	**MSE**	**MedAE**
XU-100	**RF**	0,4982	0,3580	0,4524
	ANN	0,3395	0,1900	0,2708
B1	**RF**	0,5581	0,5072	0,4693
	ANN	0,5022	0,4370	0,4167
B2	**RF**	0,3561	0,2028	0,2994
	ANN	0,2799	0,1385	0,2223
B3	**RF**	0,6385	0,5872	0,5504
	ANN	0,5119	0,4356	0,4071
B4	**RF**	0,5429	0,4445	0,4847
	ANN	0,3797	0,2386	0,3081
B5	**RF**	0,4897	0,3872	0,4363
	ANN	0,4056	0,2837	0,3364
B6	**RF**	0,7116	0,6709	0,7142
	ANN	0,2748	0,1073	0,2679
B7	**RF**	0,4915	0,3952	0,3985
	ANN	0,4086	0,2795	0,3442
B8	**RF**	0,5049	0,3774	0,4563
	ANN	0,4393	0,3307	0,3433

Conclusion

In this study, we tried to evaluate the importance and ranking of technical analysis variables in Turkish banking sector. Within this scope, 8 Turkish banks in BIST 100 index were analyzed. In addition to this issue, 10 selected technical variables were used for the period between 2010 and 2015. Furthermore, we used Random Forest method in order to achieve this objective.

Moreover, two predictive models utilizing Random Forest and Artificial Neural Networks (ANN) were built so as to predict BIST-100 index and bank closing prices. The results of these models were also compared by three metrics which are named as Mean Absolute Error (MAE), Mean Square Error (MSE), Median Absolute Error (MedAE). As a result of the analysis, it was determined that moving average (MAV-100) is the most important variable for both BIST -100 index and bank closing prices. Another result of this study is that Artificial Neural Networks ANN shows better performance for all metrics.

According to the results of the study, it can be said that in order to predict BIST-100 index and bank closing prices, investors should firstly focus on moving average value as a technical analysis indicator. Within this context, moving average value for 100 days period will give the best information to the investors. Therefore, the stock prices of the banks should be compared with moving average values. If the stock price is greater than MAV(100) value, this means that the prices will increase. Therefore, this situation should be accepted as a selling signal. Moreover, the opposite condition should also be used as a buying signal.

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