

A Stock Selection Model Based on Fundamental and Technical Analysis Variables by Using Artificial Neural Networks and Support Vector Machines

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Abstract: The basic aim of this article is to provide a model to explain stock performance utmost level. To reach this purpose, at the initial step, the model results composed of fundamental and technical analysis variables considered separately; in the second step, building the model composed of fundamental and technical analysis parameters which has best explaining ability was the focal point of this study. Artificial Neural Network (ANN) is an approach that has been widely used for financial classification problems for a long time. In addition, promising results of a novel machine learning method known as the Support Vector Machines (SVM) have been presented in several studies compared to the ANN. The stock performance results relying on fundamental analysis have shown more successful classification rates than the models based on technical analysis. Moreover, it was also experienced that the models constructed by using SVM method in the both type of analyses have shown more prominent results.

JEL Classifications: G10, G11, C10

Keywords: Stock selection, Fundamental analysis, Technical analysis, Support vector machines, Artificial neural networks

1. Introduction

With the globalization, increasing technological opportunities have brought easier access to the data. According to the Efficient Market Hypothesis, investors can obtain all stock market data in the decision making process and stock prices reflect all the information. From the financial aspect, by means of this capability, investors that analysis available data effectively can give more accurate decisions. Thus, defining the most significant parameters for the most proper investment timing is a vital issue for the stock selection.

Generally, investors try to analyze companies on the basis of discounted cash flow valuation/real options methodology and time the market. So, they try to select undervalued companies according to several criteria (Vishwanath and Krishnamurti, 2009).

Most trading systems for stock selection can be characterized as technical, fundamental or hybrid technical-fundamental systems, depending on whether they address timing and value concerns, or a combination of timing and value concerns. Statistical procedures such as analysis of variance and multiple regression analysis can help us identify and organize optimal combinations of variables for the prediction of future share-price gain in stocks in spite of weaknesses that arise when the data observed fail to satisfy the assumptions underlying use of those methods (Henning, 2010).

The stock selection process thus requires both breadth of inquiry and depth of analysis. It is achieved by starting with a full range of stocks and examining variables that intersect many dimensions, from the fundamental to the psychological, and from the stock-specific to the macroeconomic parameters (Jacobs and Levy, 2000).

Although there are several studies about stock selection, most of them focus on only fundamental or technical analysis. Besides this, in the literature no empirical study which compares ANN and SVM stock selection performances could be found. Moreover, most studies are also limited to use only stock index parameters instead of stock based financial and technical variables.

In the literature review it has been determined that ANN can be used for time series forecasting (Kaastra and Boyd, 1996; McGreal *et al.*, 1998; Zhang and Qi, 2005), classification (Ozkurt and Camci, 2009; Moavenian and Khorrami, 2010; Redgwell *et al.*, 2009; Chaplot *et al.*, 2006), clustering (Ravi *et al.*, 2006; Chan, 2005), prediction (Msiza *et al.*, 2008; Koca *et al.*, 2011) problems.

SVM method has a wide range of application fields such as classification (Chapelle *et al.*, 1999; Li, 2002; Tong and Koller, 2002; Furey *et al.*, 2000), regression (Collobert and Bengio, 2001; Vapnik *et al.*, 1997), clustering (Ben-Hur *et al.*, 2001; Chen *et al.*, 2009), recognition (Pontil and Verri, 1998; Ganapathiraju *et al.*, 1998; Huang *et al.*, 2002), medical (Brown *et al.*, 2000; Burbidge *et al.*, 2001; Guyon *et al.*, 2002; Yu *et al.*, 2010), control systems (Shiue and Ren, 2009), fraud detection (Abbasi and Chen, 2009).

It was detected in the stock selection literature review that since the stocks being traded in the stock exchange are from the different industries, the need for defining common fundamental analysis variables for all of the stocks is a difficult task. It was also exposed that the studies on the technical analysis are usually limited with the prediction of the stock index or its direction.

In this context, it was noticed that financial parameters utilized in researches are limited to several variables. Furthermore using both of fundamental and technical analysis parameters have not been examined together in a model for stock selection. In this research a wider range of financial parameters are included in model compared to related researches.

After defining common technical analysis parameters for all stocks in Istanbul Stock Exchange (ISE) 30 index, comparative ANN and SVM results were investigated based on technical and fundamental analysis process. In this way, it is possible to determine accuracy of the models based on fundamental and technical analysis variables by the years.

The essential aim of this study is to build an optimal financial model that classifies stocks into two categories as top 10 and others. In this research, both of fundamental and technical analysis parameters for each stock in ISE- 30 index have been used.

2. Theoretical Background

2.1 Artificial Neural Networks (ANN)

A neural network is a massively parallel distributed processor made up of simple processing units, which has a natural propensity for storing experiential knowledge and making it available for use. It resembles the brain in two respects:

- (1) Knowledge is acquired by the network from its environment through a learning process;
- (2) Interneuron connection strengths, known as synaptic weights, are used to store the acquired knowledge (Haykin, 1999).

A typical ANN includes a number of interconnected artificial processing neurons called nodes, each connected together in layers. Figure 1 shows three layer ANN. The numbers of nodes in input and output layers are identified by problem's nature. The number of hidden layers and the nodes within each layer is determined by trial and error process.

Hidden Units receive a weighted sum of the inputs and apply an activation function to the sum. The output units then receive a weighted sum of the hidden unit's output and apply an activation function to this sum. Information is passed only from one layer to the next. There are no connections within layers and no connections to pass information back to a previous layer (Warner and Misra 1996).

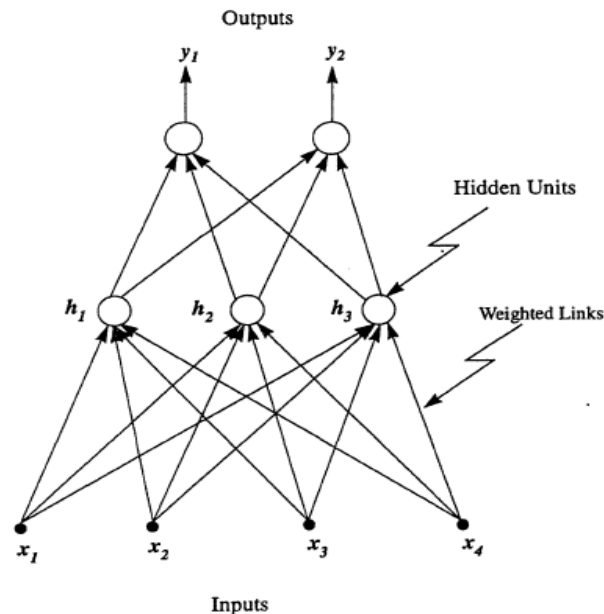


Figure 1. A schematic representation of a multilayer feed-forward neural network

Source: Warner, B., and Misra, M. (1996), "Understanding Neural Networks as Statistical Tools", *The American Statistician*, 50(4): 284-293.

Net input can be calculated as follow:

$$netinput_i = \sum_j (w_{ij} * output_j) + \mu_i \quad (1)$$

Where w_{ij} are weights connecting neuron j to neuron i , and μ_i is the threshold value for neuron i .

Each node calculates its net input and applies an activation (transfer) function to it. Different nonlinear functions have been used in models, but the most common is sigmoid function (S-Shaped) which restricts nodes outputs between 0 and 1 such as:

$$g(\text{netinput}) = \frac{1}{1 + e^{-\text{netinput}}} \quad (2)$$

The neuron receives a weighted sum of inputs (netinput) from connected units, and outputs a value of one (fires) if this sum is greater than a threshold. If the sum is less than the threshold, the activation function outputs a zero value.

$$\Theta(\text{netinput}) = \begin{cases} 1 & \text{if } \text{netinput} \geq 0 \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

Finally output of neuron i namely (y_i) can be defined as follow:

$$y_i = \Theta \left(\sum_j w_{ij} x_j - \mu_i \right) \quad (4)$$

w_{ij} : weight from neuron j to neuron i ; x_j : output of neuron j ; μ_i : threshold for neuron i , and Θ : activation function.

2.2 Support Vector Machines (SVM)

The support vector machines (SVM) approach was first introduced by Vladimir Vapnik (Vapnik, 1995). SVM emerged from researches in statistical learning theory on how to regulate generalization, and find an optimal trade off between structural complexity and empirical risk (Kara *et al.*, 2011). SVM is an inductive machine learning technique based on Vapnik's the structural risk minimization (SRM) principal implementation that aims at minimizing the true error and performs classification by constructing a hyper plane that optimally separates the data into two categories. Optimal separating hyper plane correctly classifies data points as much as possible and separates the points of two classes as far as possible, by minimizing the risk of misclassifying the training samples and unseen test samples (Farquad, 2010). In Figure 2, support vectors are shown as circled (Burges, 1998).

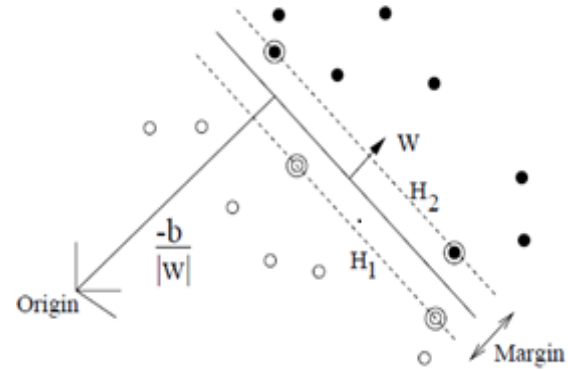


Figure 2. Linear separating hyper planes for the separable case

Source: Burges, C.J.C. (1998), "A Tutorial on Support Vector Machines for Pattern Recognition", *Data Mining and Knowledge Discovery*, 2: 121–167.

Central to SVM is the notion of kernel function, a mapping of variables from its original space to a higher-dimensional space in which the problem is expected to be solved less effortlessly. Intuitively, the kernel represents the similarity between two data observations (Belanche, *et al.*, 2007).

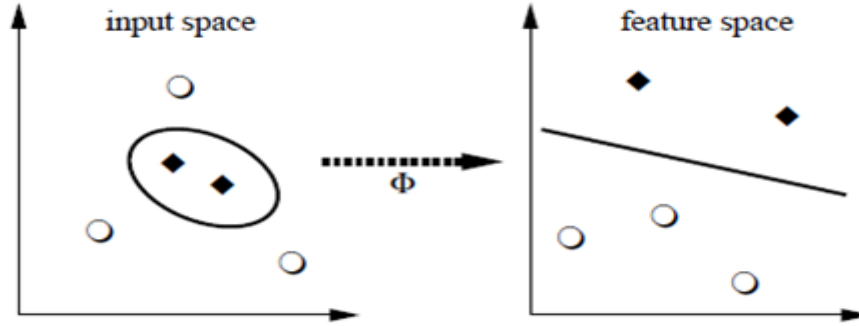


Figure 3. Mapping from input space to feature space

Source: Scholkopf, B., and Smola, A.J. (2002), *Learning with Kernels Support Vector Machines, Regularization, Optimization and Beyond*, Boston: MIT Press.

The idea of SVM maps the training data into a higher-dimensional feature space via Φ , and constructs a separating hyper plane with maximum margin there. This yields a nonlinear decision boundary in input space (Figure 3). By the use of a kernel function, it is possible to compute the separating hyper plane without explicitly carrying out the map into the feature space (Scholkopf and Smola, 2002).

There are many possible kernels, and the most popular ones are given in Table 1.

Table 1. Popular Admissible Kernels

Assume that we have empirical data for a two class training problem $(x_1, y_1), \dots, (x_N, y_N) \in X \times \{\pm 1\}$. Here X is a nonempty set that inputs $x_i \in R^d$ ($i = 1, 2, \dots, N$) are taken. $y_i \in \{-1, +1\}$ ($i = 1, 2, \dots, N$) is corresponding label. In a learning problem aim is providing generalization to unseen data points. This means that given some new $x_i \in X$ we want to predict corresponding label $y_i \in \{\pm 1\}$.

Kernel Functions	Type of Classifier
$K(x, x_i) = (x^T x_i)$	Linear
$K(x, x_i) = [(x^T x_i) + 1]^d$	Polynomial of degree d
$K(x, x_i) = \exp\left(-\frac{\ x - x_i\ ^2}{2\sigma^2}\right)$	Gaussian Radial Base Function (RBF)
$K(x, x_i) = [(x^T x_i) + b]$	Sigmoidal

Decision function of the SVM classifier is given as:

$$f(x) = \text{sgn}\left(\sum_{i=1}^N y_i a_i \cdot K(x, x_i) + b\right) \quad (5)$$

To find a_i coefficients, the quadratic programming problem below should be solved.

$$\begin{aligned} \max \quad & \sum_{i=1}^N a_i - \frac{1}{2} \sum_{i=1}^N \sum_{j=1}^N a_i a_j \cdot y_i y_j K(x_i, x_j) \\ \text{subject to} \quad & 0 \leq a_i \leq c \quad \text{and} \quad \sum_{i=1}^N a_i y_i = 0 \end{aligned} \quad (6)$$

Here c is called regularization parameter which controls the trade-off between classification error minimization and margin maximization. The a_i coefficients are called Lagrange multipliers and represent support vectors which define optimal separating hyper plane.

3. Literature Review

Some recent ANN studies in the field of financial applications can be listed as follow:

Zhu *et al.* (2008) investigated whether trading volume can significantly improve the prediction performance of neural networks under short, medium and long term forecasting horizons. Maciel *et al.* (2010) analyzed neural networks for financial time series forecasting, specifically, their ability to predict future trends of North American, European, and Brazilian stock markets. Kohara *et al.* (1997) investigated ways to use prior knowledge and neural networks to improve stock price prediction ability. Kim and Han (2000) proposed genetic algorithms approach to feature discretization and the determination of connection weights for artificial neural networks to predict the stock price index. Olson *et al.* (2003) compared neural network forecasts of one-year-ahead Canadian stock returns with the forecasts obtained using ordinary least squares and logistic regression techniques. Chen *et al.* (2003) used probabilistic neural network to forecast the direction of Taiwan Stock Exchange index.

Some researchs also have been demonstrated that SVM is a powerful tool for financial applications:

Tay and Cao (2001) examined the feasibility of SVM in financial time series forecasting by comparing it with a multilayer backpropagation neural network. Huang *et al.* (2004) used SVM to the credit rating analysis problem in attempt to provide a model with better explanatory power. Kim (2003) applied SVM to predicting the stock price index and examined the feasibility of applying SVM in financial forecasting by comparing it with backpropagation neural networks and case-based reasoning. Shin *et al.* (2005) investigated the efficacy of applying support vector machines to bankruptcy prediction problem. Min and Lee (2005) applied SVM to the bankruptcy prediction problem in an attempt to suggest a new model with better explanatory power and stability. Yang *et al.* (2002) applied Support Vector Regression to financial prediction tasks. Huang *et al.* (2005) investigated the predictability of financial movement direction with SVM by forecasting the weekly movement direction of NIKKEI 225 index. Sansom *et al.* (2003) presented an analysis of the results of a study into spot electricity price forecasting utilising Neural Networks and Support Vector Machines. Pai and Lin (2005) proposed a hybrid methodology that exploits the strength SVM model in forecasting stock prices problems. Zhou *et al.* (2004) an accurate online support vector regression method is applied to update the energy price forecasting model. Chen and Shih (2006) proposed an automatic classification model for issuer credit ratings, a type of fundamental credit rating information, by applying SVM method. Chen *et al.* (2006) applied SVM and backpropagation neural networks for forecasting the six Asian stock markets.

Ince and Trafalis (2004) used technical indicators with principal component analysis in order to identify the most influential inputs in the context of the stock price forecasting model and applied Neural networks and support vector regression with different inputs. Kamruzzaman *et al.* (2003) investigated the effect of different kernel functions, namely, linear, polynomial, radial basis and spline on prediction error measured by several widely used performance metrics of SVM models for predicting foreign currency exchange rates. Ongsritrakul and Soonthornphisaj (2003) demonstrated the use of Support Vector Regression techniques for predicting the cost of gold by using factors that have an effect on gold to estimate its price. Yu *et al.* (2005) proposed a hybrid intelligent data mining methodology, genetic algorithm based support vector machine model to explore stock market tendency.

Recent studies which include technical and fundamental analysis parameters can be presented as follows:

Lam (2004) investigated the ability of neural networks, specifically, the backpropagation algorithm, to integrate fundamental and technical analysis for financial performance prediction. Leigh *et al.* (2002) showed the potential that lies in the novel application and combination of methods to evaluate stock market purchasing opportunities using the “technical analysis” school of

stock market prediction. Yao *et al.* (1999) presented a study of artificial neural networks for use in stock index forecasting in Kuala Lumpur Stock Exchange. Mehrara *et al.* (2010) used moving average crossover inputs based on technical analysis rules for forecasting stock price index in Tehran Stock Exchange. Elleuch (2009) examined whether a simple fundamental analysis strategy based on historical accounting information can predict stock returns. Fan and Palaniswami (2001) attempted to use SVM to identify stocks that are likely to outperform the market by having exceptional returns given the fundamental accounting and price information of stocks trading on the Australian Stock Exchange. Han *et al.* (2007) proposed a method by using SVM with financial statement analysis for prediction of stocks. Qi and Maddala (1999) showed whether the ability of stock returns by means of linear regression can be improved by a neural network. Singh *et al.* (2011) examined the casual relationship between index returns and certain crucial macroeconomic variable namely employment rate, exchange rate, GDP, inflation and money supply for Taiwan.

4. Data and Methodology

After the 2000 and 2001 financial crises in Turkey, both real and financial sector had a serious experience in the restructuring period. Along with this positive effect, with the recovery of the real sector in Turkey, the interest of both domestic and foreign investors to the stocks traded in ISE has started to increase during this period. In this context, the investigation of the data collected between 2002 and 2010 periods is more meaningful.

The performance results of the companies subject to the ISE 30 index according to years were estimated by means of fundamental and technical analysis parameters. For this purpose, as of year-end, the top 10 stocks yielding the highest return rate were labeled as “1”, and the rest were labeled as “0” annually.

In the constructed model, set of best representing independent variables was determined for the whole of companies with heterogenic nature in the ISE 30 index during the period of 2002-2010. By this way, the situation of whether the ISE 30 stocks would be among the first 10 or not was determined by means of the Multi Layer Perception method (MLP) that is type of the ANN and the SVM method.

Application of data dimensionality reduction pre-processing step prior to the classification procedure does improve the overall classification performance. Furthermore, feature selection can also provide a better understanding of the underlying process that generated the data. In other words, through feature selection, we have the opportunity in uncovering the essential features (Wu *et al.*, 2008).

In next step of the study, to build up set of independent variables which can represent return rate performance of the stocks in the highest level, by implementing feature selection to the variables group which also includes fundamental and technical variables together, fundamental and technical analysis parameters were revealed as a result of dimension reduction. As it was stated before, mentioned steps were illustrated in the flow chart below (Figure 4).

The data used in the model were gathered from two different resources. Beside the ratios obtained from the basic financial statements such as balance sheet and income statement, there are also variables related to the stock market value. For the stock performance measurement according to the fundamental analysis, there are 14 essential indicators determined to represent the ISE 30 index companies from different industries as a whole. To obtain the stock performance variables based on the technical analysis, the MetaStock software was employed. The technical data is composed of 12 indicators from the ISE 30 index companies between 2002 and 2010 period. The detailed information was given below.

Fundamental indicators in the model are Mass Index (*MASS*), Average True Range (*ATR*), Momentum (*Mo*), Chaikin Money Flow Indicator (*CMF*), Commodity Channel Index (*CCI*), Moving Average Convergence-Divergence Trading Method (*MACD*), Exponential Moving Average (*EMA*), Relative Strength Index (*RSI*), Money Flow Index (*MFI*), Stochastics (*Stoch*), Triple exponential smoothing of the log of closing price (*TRIX*), Williams %R (*Will_R*). Technical variables are Growth in assets, Growth in net profit, Equity growth, Current assets/assets, Fixed assets/assets, Equity/Assets, Equity / tangible assets, Return on Assets, Net profit / current assets, Return on equity, Earnings per share, Price-earnings ratio, Market to book value.

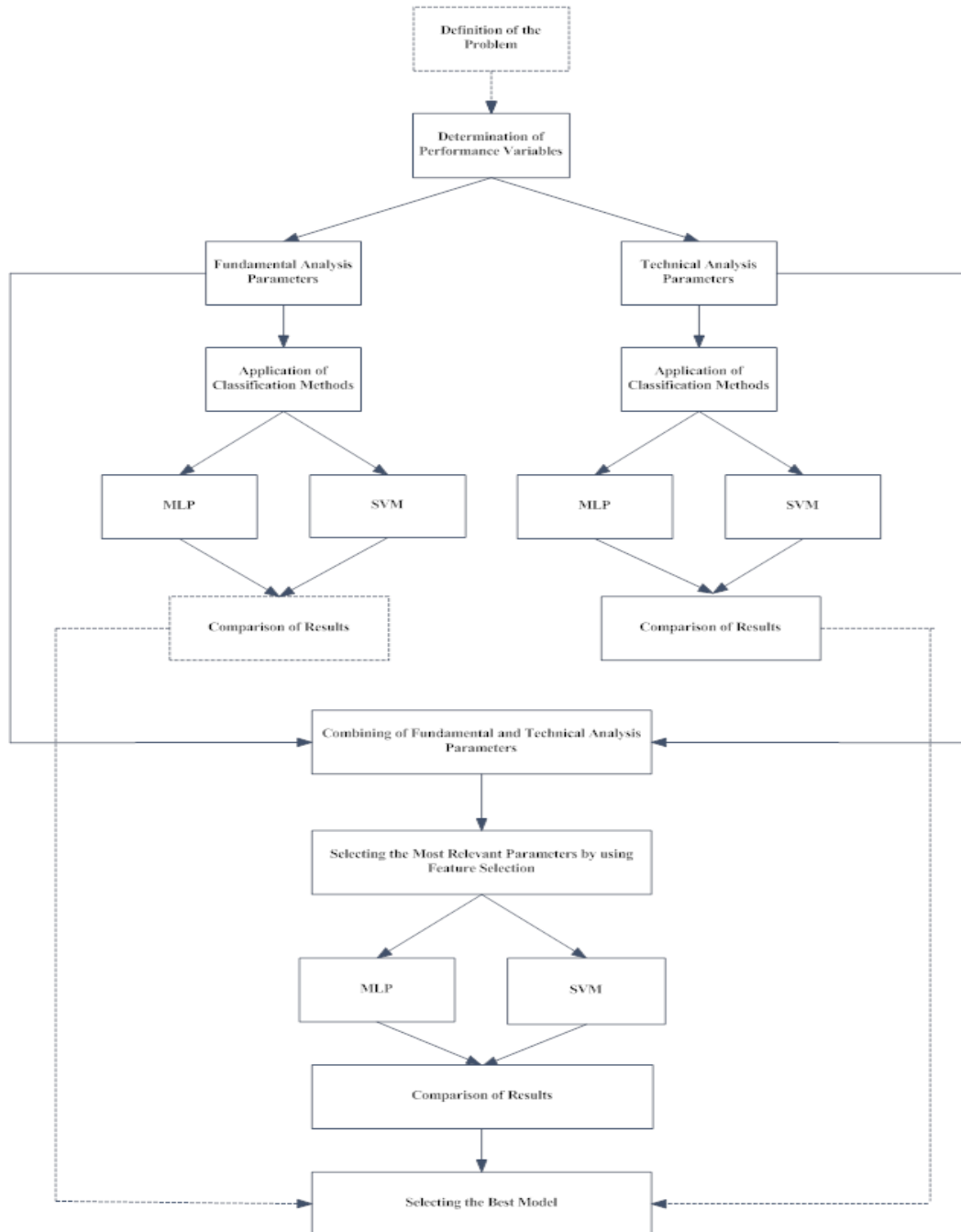


Figure 4. Flowchart of the model presented

5. Empirical Results

For the annual stock performance measurement based on the technical and fundamental analysis, the first 2 years were used as training set, and the following year was used as test set. In this context, for example, years of 2002 and 2003 were for training and year 2004 was test set. MLP with the most proper architecture for each training set; and the SVM models showing the highest successful classification ratio according to the different kernel types were taken into account during the investigation.

To construct MLP models, Automated Neural Networks Module of the STATISTICA 8.0 package was employed. In the ANN models using entire data set were spited randomly for the training, test and validation sets as 70, 20 and 10 percentage respectively. The biggest advantage of the STATISTICA software is capability of searching the optimal number of hidden layer nodes in a given interval. Furthermore, it can test the different activation functions that could be used on the hidden and output layer; and can select the most successful MLP architecture.

By using SVM module, different kernel types such as Linear, Polynomial, Sigmoidal, and Radial Based Function (RBF) can be tested. In the SVM models, created by the feature selected variables, 75% of the data set is used for training, 25% for the testing purposes.

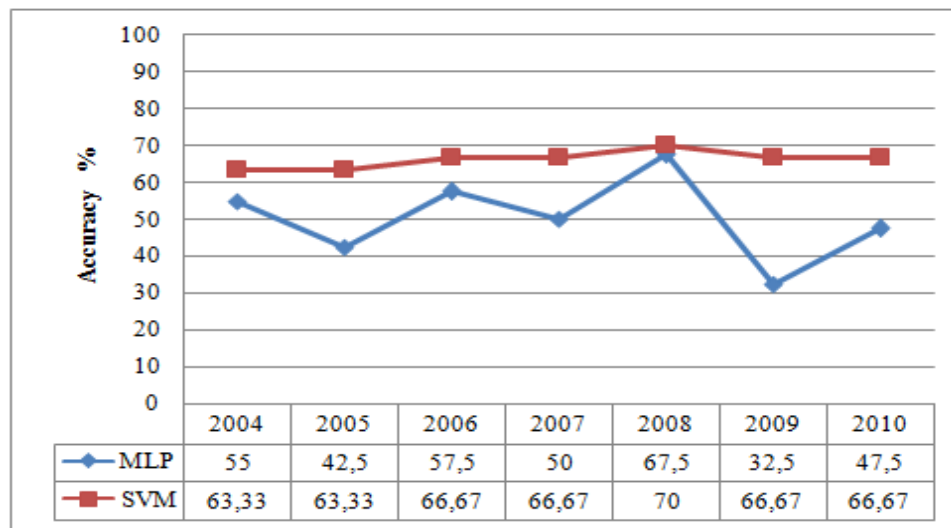


Figure 5. Results of technical analysis

As it can be seen in the figure 5, results of the model based on the SVM give superior results obtained based on the MLP for each year. In general, although the annual SVM results are close to each other, annual performance of the MLP models shows instability. In both methods, it was noticed that the highest classification performance results were seen in 2008 test set (for MLP, 67.5%; and for SVM, 70%).

Furthermore, when the annual averages of the models comprising technical analysis variables were taken, the resultant success rate for the MLP was 50.36% and for the SVM was 66.19%.

In general, except the year 2007, the SVM performance results have higher success rates compared to the results of the MLP models. Moreover, in both models, the performance results show fluctuations. Within the investigation period, both models showed results that can be considered rather high test performance in 2005 (MLP 90%, SVM 96.66%) (Figure 6).

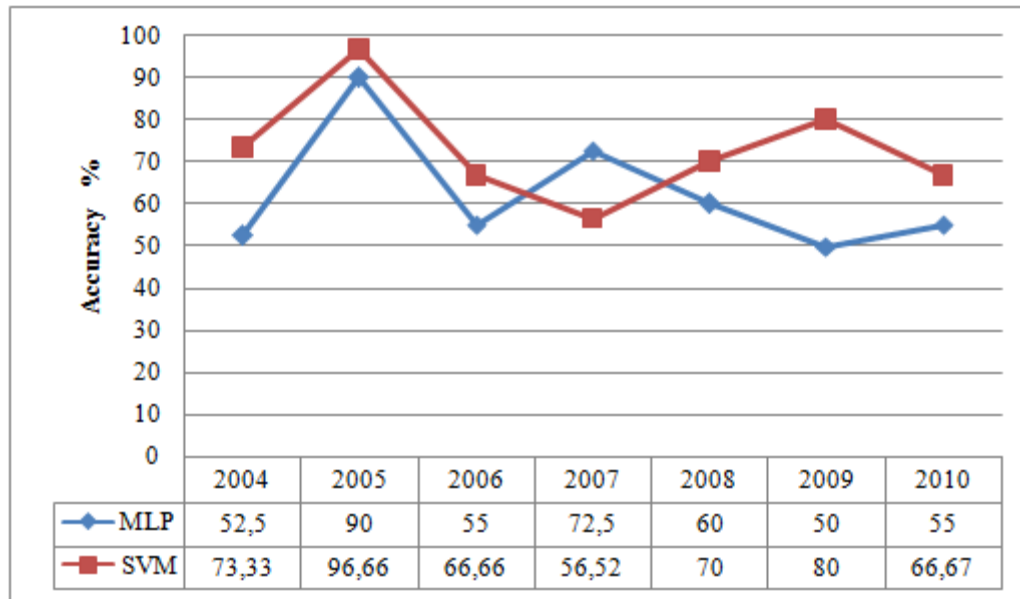


Figure 6. Results of fundamental analysis

The average success rate of the models in which the fundamental analysis variables used were 62.14% and 72.83% for MLP and SVM respectively.

When the study is considered according to the methods, it can be seen that general results are in the favour of fundamental analysis. As of years, the highest success was determined in 2005 among the results of the fundamental analysis; and in 2008 among the results of the technical analysis (Figure 7).

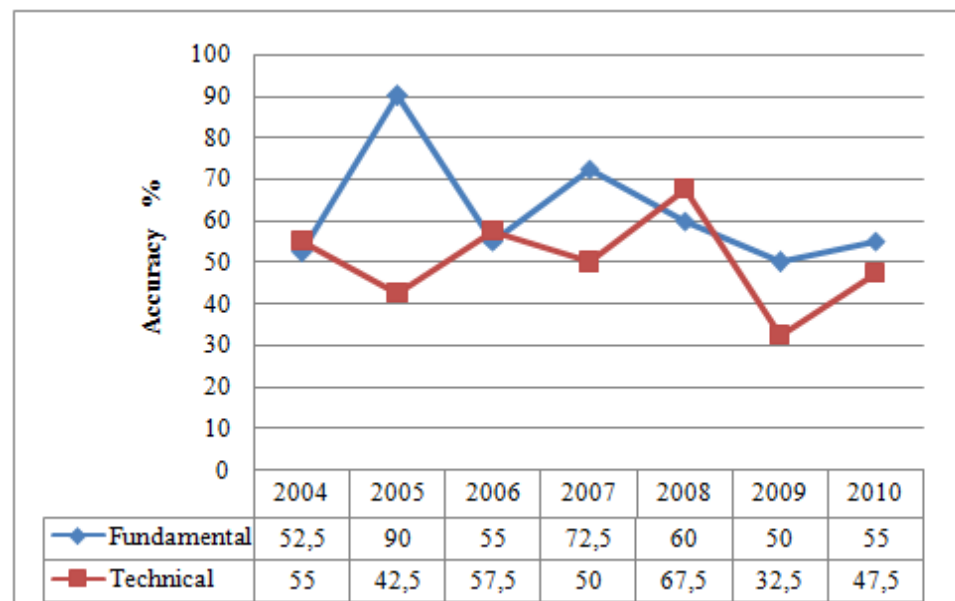


Figure 7. MLP analysis results

The general performance results of the SVM models with both technical and fundamental analysis variables have shown higher average success rate than the models based on MLP method. Moreover, in the SVM analysis results, the models including technical analysis variables have shown close values to each other as of years (Figure 8).

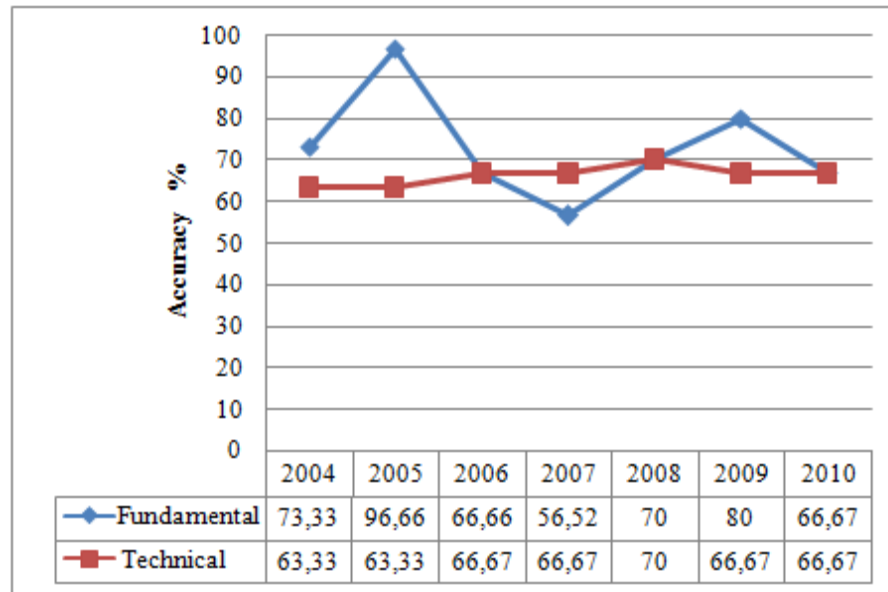


Figure 8. SVM analysis results

Usually, in the statistical studies, inclusion of the insignificant variables into the model may increase the complexity of the model. To prevent or minimize this situation, the variables in the model with the highest significance can be determined by the feature selection algorithms.

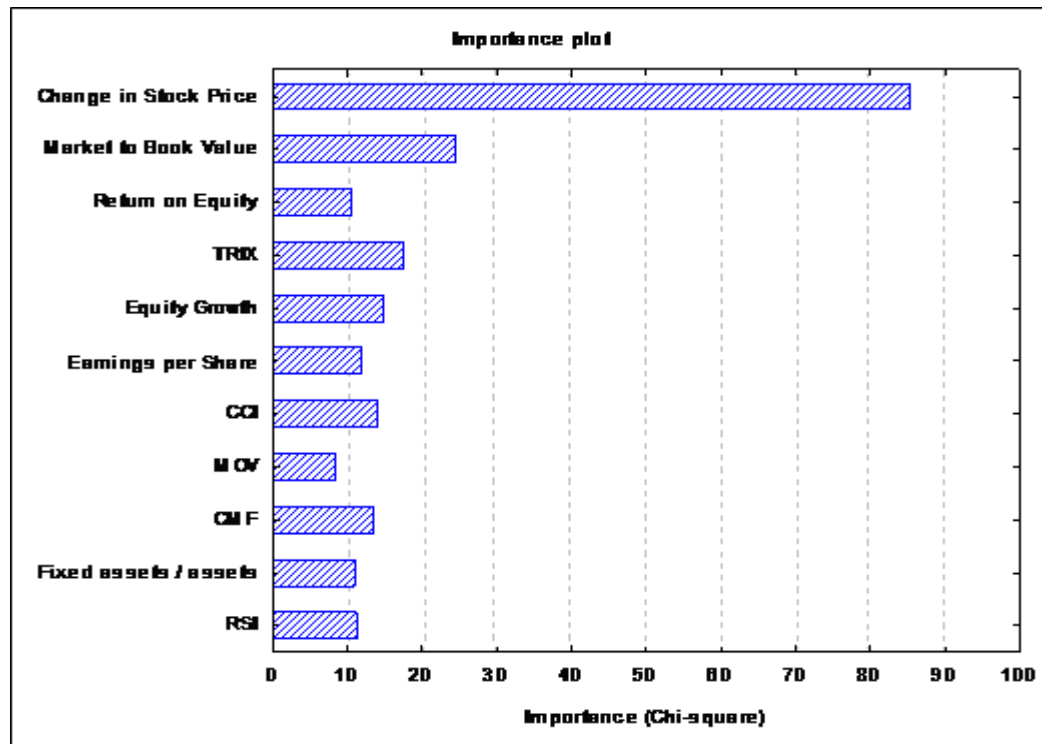


Figure 9. Results of feature selection

At that end, among the independent variables based on technical and fundamental analysis, the variables that can represent performance results of the stocks at maximum level were selected by the modules called “Feature Selection” and “Variable Screening” in the STATISTICA 8.0. As a result of the Feature Selection process, 26 variables comprised of 14 fundamental and 12 technical ones were reduced to the total of 11 variables. These variables are in the Figure 9 according to their importance.

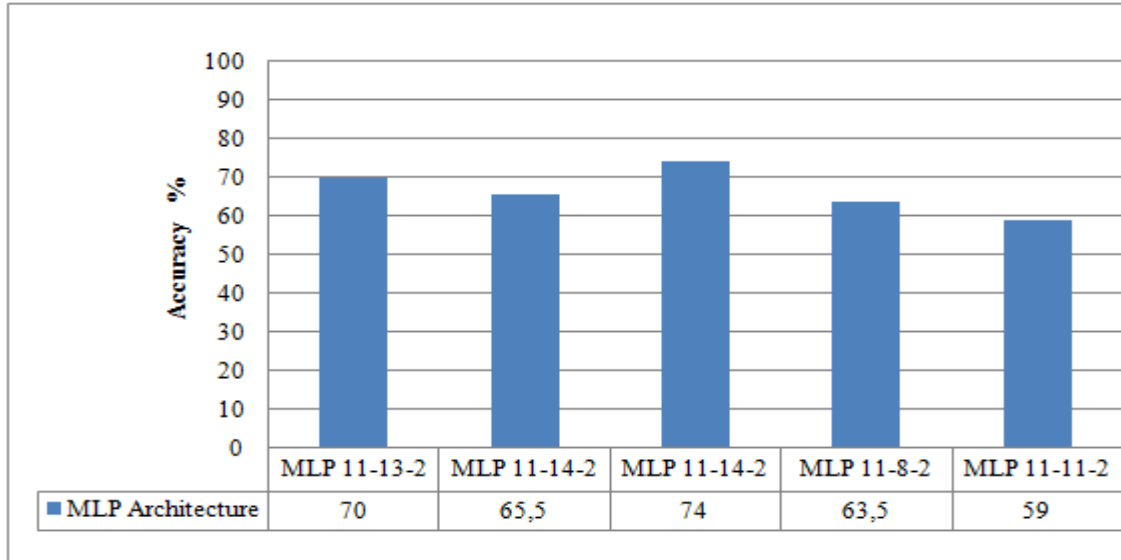


Figure 10. MLP results (2002-2007 training set; 2008-2010 testing set)

Five different MLP models giving the best results on the data set built by applying Feature Selection were shown in figure 10. To construct effective models on all of the data sets, while 2002-2007 periods was taken as the training set and 2008-2010 period was taken as the test set. The highest success rate (74%) was shown by the MLP model with the 11-14-2 architecture. Besides, as it was expected, MLP model results were close to each other.

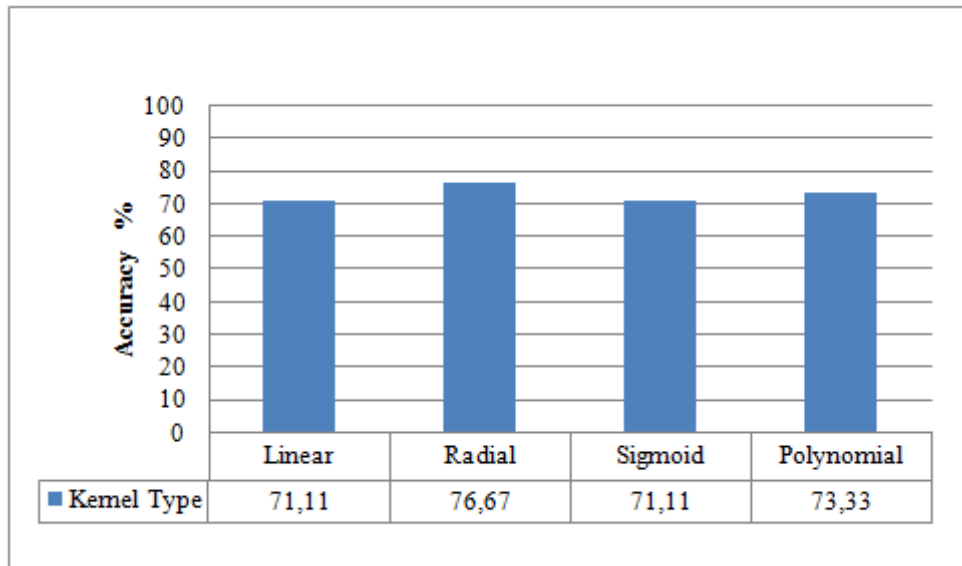


Figure 11. SVM results for different kernel types (2002-2007 training set; 2008-2010 testing set)

Table 2. *t*-test results of MLP and SVM models

SVM models with different kernels were formed on the same data set mentioned above (Figure 11). According to the results, just same as the MLP models, it was observed that SVM models also give results close to each other. The highest success rate (76.67%) was obtained for the SVM model using the radial kernel.

Table 2 shows that the difference between mean performances of models is significant at $\alpha = 0.05$ significance level. This means that the performance of the SVM models is significantly better than the performance of the MLP models.

Model	MLP	SVM
Mean	66.4	73.055
Variance	33.675	6.9033
N	5	4
d.f.	6	
<i>t</i>	2.28792	
<i>P</i>	0.03106	

6. Conclusions

By the knowledge based economy investment decisions in the stock markets have been started to be more complex due to huge amount of economic and financial data. Stock market efficiency causes existing share prices to always incorporate and reflect all relevant information. Thus studying with the most appropriate data and timing in financial decisions has advantages for investors in the competitive environment. In this scope, the study aims to find best performing model using both technical and fundamental analysis variables.

In the research, there is an evident difference observed between the performance results of the SVM and the MLP models produced with the variables based on the technical and fundamental analysis, it was noticed that the performance difference between SVM and MLP models created by application of feature selection decreased significantly. Furthermore, the model presenting the best performance emerged with the SVM method from the variable set produced as a result of the feature selection application just same as it happened to the performance results based on the technical and fundamental analyses before.

As it can be understood from the results, the stock performance results relying on the fundamental analysis have higher success rate than the models relying on technical analysis data. Moreover, in both analysis types, it was observed that the models created by means of the SVM method are presenting more successful results. When the variable set produced by means of the technical and the fundamental analyses data as a whole was reduced to 11 variables through the feature selection module, at the end of the investigation of the resultant model, it was determined that it over performed the averages of separate models based on the fundamental and the technical analyses.

Consequently a novel hybrid model with the most explanatory power has been developed by using data set which obtained after dimension reduction process of technical and fundamental analysis variables.

This study can also be applied to industrial based data set for further research. In addition fundamental and technical analysis variables of companies in ISE 30 index can be investigated together with other countries stock market data. Thus by cross countries variables, comparative results for both stocks and countries can be attained alternatively in the future.

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