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A Hybrid Model to Forecast Stock Trend Using Support Vector Machine and Neural Networks

*J Sharmila Vaiz[1], M Ramaswami[2]
[1] *Ph.D. Research Scholar, Department of Computer Applications, Madurai Kamaraj University, Madurai, India.*
[2]*Associate Professor, Department of Computer Applications, Madurai Kamaraj University, Madurai, India.*
*Corresponding Author: *J Sharmila Vaiz*

ABSTRACT:- Machine learning methods have trouble when dealing with large number of input features, which is posing an interesting challenge for researchers. Pre-processing of the data is very much essential in order to use machine learning methods effectively. Relevant feature selection has become an essential task that speeds up data mining algorithms, improves predictive accuracy and increases comprehensibility. In this study, a novel approach is proposed by combining both Support Vector Machine (SVM) and Artificial Neural networks (ANN) in predicting stock trend. SVM technique is introduced to remove irrelevant and redundant variables and subsequently neural network based classification technique is used to forecast stock trends with the reduced feature set. Importance of choosing correct input features using SVM before classification is reflected using evaluation measures accuracy, F-measure, ROC curves and AUC.
Keywords:- Feature selection, classification, prediction, stock trend, technical analysis

I. INTRODUCTION

The study of the human brain is thousands of years old. With the advent of modern electronics, researchers try to harness this thinking process. The first step toward artificial neural networks came in 1943 when Warren McCulloch [24], a neurophysiologist, and a young mathematician, Walter Pitts[24], wrote a paper of how neurons might work. They modelled a simple neural network with electrical circuits. Today, neural networks discussions are occurring everywhere. The simplest definition of artificial neural networks (ANN) is provided by the inventor of the first neuro computer, Dr. Robert Hecht-Nielsen [25]. He defines a neural network as: *"...a computing system made up of a number of simple, highly interconnected processing elements, which process information by their dynamic state response to external inputs.*

ANN is modelled after the neuronal structure of the mammalian cerebral cortex but on much smaller scales. A large ANN might have hundreds or thousands of processor units, whereas a mammalian brain has billions of neurons with a corresponding increase in magnitude of their overall interaction and emergent behaviour. Neural networks are typically organized in layers. A three layer neural network [19] has been proved to be a universal function approximation and finds its use in a number of fields like sales forecasting, data validation, customer research, price forecasting, medicine etc.

The amount of high dimensional data is publicly available on the internet has greatly increased in the past few years. Training machine learning methods is a difficult task on a huge dimensional data. This calls for feature selection method that removes irrelevant, redundant and noisy data and also useful to increase accuracy, decrease running time requirements while training with machine learning models. SVM have been extensively used as a classification tool with a great deal of success from object recognition [12, 13] to classification of cancer morphologies and a variety of other areas. In this article we introduce feature selection algorithms for SVM.

There are several forecasting models used by stock analyst. Most widely used conventional methods to forecast stock markets include auto regressive (AR), Auto-Regressive Moving Average (ARMA), Auto-Regressive Integrated Moving Average (ARIMA), Generalized Auto-Regressive Conditional Heteroscedasticity (GARCH) and Stochastic Volatility (SV)[23]. With the emergence of machine learning and artificial intelligence algorithms it is possible to tackle computationally demanding mathematical models in stock price direction prediction. Frequently adopted methods include artificial neural networks (ANN), Bayesian networks and support vector machine (SVM) [9, 10].

In this study, a comparative study is made to show the effectiveness of feature selection using SVM in ANN machine learning classification.

II. SURVEY OF LITERATURE

Saahil Madge[1] in his study used SVM to predict the stock trend of 34 technology stocks. He derived the features price volatility and momentum for individual stocks and for the overall sector from closing prices of the stocks. He concluded that there is a little predictive ability in short term but definite predictive ability in long term.

Xinjie Di[2] attempts to forecast stock trend of 3 companies Apple, Amazon and Microsoft. He used Williams%R, Rate of Change(ROCR), Momentum(MOM), Relative Strength Index(RSI), Commodity Channel Index(CCI), Average Directional Index(ADX), Triple Exponential Moving Average(TRIX), Moving Average Convergence Divergence(MACD), On Balance Volume(OBV), Time series Forecasting(TSF), Average True Range(ATR), Money Flow Index(MFI). These indicators are computed against different periods from 3 days to 20 days and each of them is treated as individual feature space. Further, Extremely Randomized Tree Algorithm is used to obtain reduced feature set from the set of 84 attributes. Subsequently a model is fitted with SVM with RBF kernel and its gains predictive accuracy of above 70% for these 3 stocks.

Luca Di Persio[3] used ANN approach to predict stock market indices. They focussed their attention in predicting the trend of the index S&P500 and FOREX market. They carried down the experiments with different ANN networks such as Multi-layer Perception (MLP), the convolution Neural Networks (CNN), and the Long Short-Term Memory (LSTM) recurrent neural networks technique with the intention of predicting the trend movement up or down. They predicted the trend for S&P 500 index from the past n days and FOREX from 1-minute time frame work data. Their findings reported that CNN performed better than other architectures and achieved with predicted accuracy of S&P500 is 62% and FOREX is 83% using CNN.

Asif Ullah Khan[4] suggested the best time to invest in the selected stocks by combining both fundamental analysis and technical analysis. They also proposed an improved method for stock picking and finding an entry point of investment using hybrid method consist of self-organizing maps(SOM) and selected technical indicators. The stocks selected by this method have given 19.1% profit in a period of one month.

Jacinta Chan Phooi Mng[5] enhanced profitability of trading rules by the use of neural networks on the Kuala Lumpur Composite Index (KLCI), a proxy of the Malaysian stock market traded in Bursa Malaysia. The profitable returns on KLCI from January 2008 to December 2014 provide a piece of evidence on the ability of technical trading rules using neural networks to out-perform the buy-and-hold threshold benchmark. The technical indicators used as inputs, besides the actual close (Ct) and previous close (Ct-1), are a simple 5-days moving average (MA5), 10-days moving average (MA10), 50-days moving average (MA50), the Resistance Strength Index (RSI), Momentum (M), and Stochastic %K and %D with the output of the next predicted close. He concluded that neural network may be used as tools in technical analysis for future price prediction.

In our previous study[6] the role of technical indicators in predicting the stock trend of six major high capitalization companies of NSE is investigated using tree based classifier algorithms such as C5.0, CART and ID3. Classification accuracy of classifier ID3, C5.0 and CART reveals that technical indicators contribute about 85% of accuracy in predicting the stock market behaviour. Performance of ID3, C5.0 and CART are analyzed with many predictive measures – predictive accuracy, F-Measure, ROC curve and AUC value.

In another attempt [7] Deep Neural Network with different activation functions to predict the stock market movement direction has studied. We compare the results of six major capitalization companies and underline the fact that Rectifier and Maxout activation function provides better accuracy than Tanh activation function. The proposed model gives maximum accuracy of 87.76% with Maxout activation function in predicting stock trend.

Several stock market forecasting methods are proposed by various authors and discussed the role of SVM, ANN and other hybrid models by combining SOM. The technical indicators used in their study are RSI, MA, Momentum, Stochastic %K and %D and Price volatility.

In this study, we used a combination of Support Vector Machine and ANN to forecast the stock trend of six companies.

III. MATERIALS AND METHODS

In this study we attempt to forecast the stock trend of six major high capitalization companies of NSE, INDIA by deploying two different soft computing approaches – SVM and ANN. Four years of daily stock price from January 2012 to December 2015 is used in this study with 22 technical indicators such as RSI, MACD, EMA values derived from OHLCV data (Open, High, Low, Close, Volume) using TTR package in R.

A. Research Data

To forecast the stock trend of six companies is selected which are most active and have high market capitalization. The selected companies are:

- Tata Consultancy Services Ltd. (TCS)
- Reliance Industries Ltd. (RIL)
- Housing Development Finance Corporation Ltd. (HDFC)
- Hindustan Unilever Ltd.(HUL)
- Sun Pharmaceutical Industries Ltd. (SPIL) and
- Imperial Tobacco Company of India Ltd. (ITCL)

B. Features Used

In Technical analysis, technical indicator is a mathematical calculation based on historic price and volume to forecast stock trend directions. Technical indicators are typically plotted as a chart pattern to predict the market movement. Examples of common technical indicators include Relative Strength Index, MACD, Bollinger Bands and Stochastic. In this study 22 technical indicators are used which is listed under table 1.

Table 1: List of Technical Indicators

1	Simple Moving Average(SMA)
2	Exponential Moving Average(EMA)
3	Weighted Moving Average (WMA)
4	Double Exponential Moving Average (DEMA)
5	Volume Adjusted Moving Average (VAMA)
6	Moving Average Convergence/Divergence(MACD)
7	Average Directional Movement Index (ADX)
8	Trend Detection Index(TDI)
9	Aroon Indicator(Aroon)
10	Vertical Horizontal Filter (VHF)
11	Relative Strength Index (RSI)
12	Stochastic Oscillator(stoch)
13	Stochastic Momentum Index(SMI)
14	William%R– Williams Percentage Range(WPR)
15	Chande’s Momentum Oscillator (CMO)
16	Commodity Channel Index(CCI)
17	Bollinger Bands(BBands)
18	Donchain channel(DC)
19	Average True Range (ATR)
20	Chaikin Money Flow(CMF)
21	On Balance Volume (OBV)
22	Money Flow Index(MFI)

C. Support Vector Machine

Support vector machine (SVM) has excellent performance on classification and prediction and is widely used on many real word problems. Moreover, SVM has also been used as a dimension reduction technique to reduce data structure complexity in order to identify important feature variables as a new set of testing instances [16]. By feature selection, inappropriate, redundant, and noise data of each problem can be filtered to reduce the computational time of classification and improve classification accuracy. The common methods of feature selection include backward feature selection (BFS), forward feature selection (FFS), and ranker [17]. SVM based feature selection methods like support vector machine recursive feature elimination (SVM-RFE), can filter relevant features and remove relatively insignificant feature variables in order to achieve higher classification performance [12]. SVM is developed from statistical learning theory[26], as based on SRM (structural risk minimization). It can be applied on classification and nonlinear regression [15]. Generally speaking, SVM can be divided into linear SVM (linear SVM) and nonlinear SVM. An illustration of linear SVM is depicted in Fig. 1.

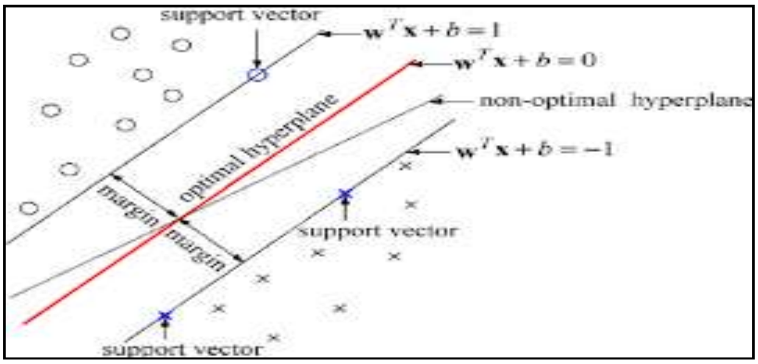

Figure 1: An Illustration of Linear SVM

Linear SVM is defined as, given a training dataset of n points of the form $(\overrightarrow{x_1}, y_1), \dots.(\overrightarrow{x_n}, y_n)$ where y_i is either -1 or 1, each indicating the class to which the point $\overrightarrow{x_i}$ belongs. Each $\overrightarrow{x_i}$ is a p-dimensional real vector. We want to find the "maximum-margin hyperplane" that divides the group of points $\overrightarrow{x_i}$ for which $y_i = 1$ from the group of points for which $y_i = -1$, which is defined as the distance between the hyperplane and the nearest point $\overrightarrow{x_i}$ from either group is maximized.

If the training data are linearly separable, we can select two parallel hyper planes that separate the two classes of data, so that the distance between them is as large as possible. The region bounded by these two hyper planes is called the "margin", and the maximum-margin hyper plane is the hyper plane that lies halfway between them. These hyper planes can be described by the equations

$$\vec{\omega}.\vec{x} - b1 \quad (1)$$

and

$$\vec{\omega}.\vec{x} - b = -1 \quad (2)$$

Geometrically, the distance between these two hyper planes is $\frac{2}{\|\vec{\omega}\|}$, so to maximize the distance between the planes we want to minimize $\vec{\omega}$. As we also have to prevent data points from falling into the margin, we add the following constraint for each i either

$$\vec{\omega}.\vec{x} - b \geq 1, \; if\; y_i = 1 \quad (3)$$

or

$$\vec{\omega}.\vec{x} - b \leq 1, \qquad if\; y_i = -1 \quad (4)$$

These constraints state that each data point must lie on the correct side of the margin.
This can be rewritten as in equation 5:

$$y_i(\vec{\omega}.\vec{x} - b) \geq 1, for\; all\; 1 \leq i \leq n \quad (5)$$

We can put this together to get the optimization problem:
"Minimize $\|\vec{\omega}\|$ subject to $y_i(\vec{\omega}.\vec{x} - b) \geq 1, for\; i = 1, \dots, n$"
The $\vec{\omega}$ and b that solve this problem determine the classifier; $\vec{x} \rightarrow sgn(\vec{\omega}.\vec{x} - b)$. An important consequence of this geometric description is that the max-margin hyper plane is completely determined by those $\overrightarrow{x_i}$ which lie nearest to it. These $\overrightarrow{x_i}$ are called support vectors.

1. Non Linear Support Vector Machine (Non linear SVM)

The original maximum-margin hyper plane algorithm proposed by Vapnik in 1963 constructed a linear classifier. However, in 1992, Bernhard E Boser, Isabelle M Guyon and Vladimir N Vapnik suggested a way to create nonlinear classifiers by applying the kernel trick (originally proposed by Aizerman[18]) to maximum-margin hyper planes. When input training samples cannot be separated using linear SVM, we can use conversion function φ to convert the original 2-dimensional data into a new high-dimensional feature space for linear separable problem. SVM can efficiently perform a nonlinear classification using what is called the kernel trick, implicitly mapping their inputs into high-dimensional feature spaces. Presently, many different core functions can effectively improve the computational efficiency of SVM. The relatively common core functions include the following four types i) linear kernel function ii) polynomial kernel function iii) radial basis kernel function and iv) sigmoid kernel function.

2. Feature Selection Based on SVM-RFE

A feature selection process can be used to remove terms in the training dataset that are statistically uncorrelated with the class labels, thus improving both efficiency and accuracy. It implies not only cardinality reduction, which means arbitrary cut-off on the number of attributes when building a model, but also the choice of attributes, which implies that the model actively selects or discards attributes based on their usefulness for analysis[21]. The subsets selected each time are compared and analyzed according to the formula assessment function. If the subset selected in step $m + 1$ is better than the subset selected in step m, the subset selected in step $m + 1$ can be selected as the optimum subset. The feature selection problem has been modelled as a mixed 0-1 integer program [11]. SVM-RFE is an SVM-based feature selection algorithm created by [12]. In addition to reducing classification computational time by reducing feature set, it can improve the classification accuracy rate [12]. In recent years, many scholars improved the classification effect in medical diagnosis by taking advantage of this method [13, 14].

D. Neural Networks

"A neural network is a massively parallel distributed processor that 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 through a learning process. 2. Interneuron connection strengths known as synaptic weights are used to store the knowledge."- Haykin (1994). ANN spiked an increased interest in machine learning models [20].

Biological neuron structure paves the way to the evolution of artificial neurons. The transmission between biological neurons through synapses is a complicated chemical process in which specific transmitter substances are released from the sending side of the junction. The effect is to raise or lower the electrical potential inside the body of the receiving cell. If this graded potential reaches a threshold, the neuron fires. It is this characteristic that the artificial neuron model attempt to reproduce. The neuron model shown in Fig. 2[19] is the one that widely used in artificial neural networks with some minor modifications on it.

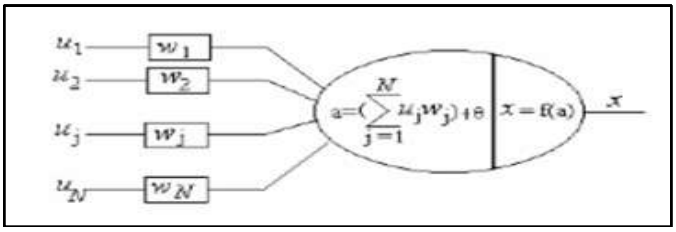

Figure 2: Artificial Neuron Model

In order to implement some Boolean functions the outputs of some neurons are fed as input to the others constituting a neural network. To discriminate between neurons indices are assigned to neurons. The activation function formula of i^th neuron is shown in equation 6. There are several types of network architectures such as feed forward, feed backward, fully interconnected, competitive net etc.

$$\alpha_i = \sum_{j=1}^{N} w_{ij}\, x_j + \theta_i \qquad (6)$$

The data is normalized before being input to the ANN. The input vectors of the training data are normalized such that all the features are zero-mean and unit variance. There are different types of activation functions of the neurons such as unipolar, bipolar, tan hyperbolic and radial basis function [17]. The target values are normalized based on the activation function. In unipolar sigmoid, they are normalized to a value between 0 and 1, if the activation function is Bipolar sigmoid or Tan hyperbolic, they are normalized to a value between -1 and 1 and 0 and $\sqrt{2\pi\sigma}$ when the activation function is RBF the test data vector is again scaled by the same factors with which the training data was normalized. The output value from the ANN for this test vector is also scaled back with the same factor as the target values for the training data.

Some stopping criterion is required to ensure that the algorithm does not run forever. The conditions can be i) the change in error from one iteration to the next falls below a threshold that the user can set ii) The error value begins to increase. There is a relaxation factor here as well that allows minimal increase as it is also observed that the error tends to increase by small amount and then decrease again. ii) If the number of iterations (or epochs) goes beyond a certain limit. In our case the limit is set to 200.

The error for convergence is calculated as the root mean squared error between the target values and the actual outputs. The same error is used to report the performance of the algorithm on the test set. Cross validation is used to measure the error of the back propagation algorithm in all iterations. It is independent of the training set and helps in a more general measure of the error and gives better results.

Artificial Neural Networks (ANN) is one of the most widely used techniques for stock prediction [22]. In this study, we considered 22 technical indicators as input variables which have been neglected by much of the researchers. SVM-RFE feature selection [21] is used to remove the redundant, irrelevant technical indicators and then the model is developed with ANN.

In this study we build the model using neural networks. Then, SVM feature selection method is applied to the dataset to reduce the dimension of the dataset and again the model is built using neural networks on the reduced feature set. Classification accuracy before and after SVM feature selection is compared using various evaluation measures.

IV. RESULTS AND SIMULATION

In our study, four years data (Open, Close, High, Low, Volume) from January 2012 to December 2015 of six companies is collected from Yahoo finance with 22 technical indicators [8] values such as RSI, MACD, etc. which are derived from OHLCV data using TTR package in R. A price change variable is calculated as the difference between Close price and Open price. If the difference is greater than 1 then it is a buy signal else it is a sell signal. Price change is chosen as the classification variable. Dataset is split into training set and test set with a probability of 80% and 20%. The neural network model is developed from the combined 22 technical indicators. The classification accuracy of neural network is shown in table 2.

Table 2: Evaluation measures of six companies HDFC, SPIL, TCS, ITC, HUL and RIL

ScriptName	Prediction Model with ANN			Hybrid Prediction Model with SVM-ANN		
	Accuracy	F-measure	AUC	Accuracy	F-measure	AUC
HDFC	0.8300	0.8061	0.9245	0.8667	0.8571	0.9499
SPIL	0.8333	0.7899	0.8829	0.8333	0.7965	0.9323
TCS	0.8167	0.7909	0.9274	0.8600	0.8250	0.9416
ITC	0.8667	0.8601	0.9413	0.8663	0.8530	0.9528
HUL	0.7800	0.7626	0.8878	0.8533	0.8321	0.9360
RIL	0.8833	0.8679	0.9590	0.9000	0.8888	0.9638

Subsequently, SVM feature selection technique assesses the effectiveness of 22 technical indicator features in classification. Four to five features are extracted using SVM feature extraction. The selected features from SVM of six companies are listed in table 3.

Table 3: Features Selected using SVM

Script Name	**Selected Technical Indicators**
HDFC	BBands, CCI, DC, WPR, SMI
SPIL	BBands, CCI, DC, WPR, RSI
TCS	BBands, CCI, DC, WPR, SMA
ITC	BBands, CCI, DC, WPR
HUL	BBands, CCI, DC, WPR
RIL	BBands, CCI, DC, WPR, VWMA

Based on the observations in table 3, it is visible that BBands, CCI, DC and WPR are strong technical indicators that plays major role in predicting the stock trend. Once again the prediction model is reconstructed with reduced feature subset. The prediction accuracy of both ANN and SVM-ANN is shown in Fig. 3.

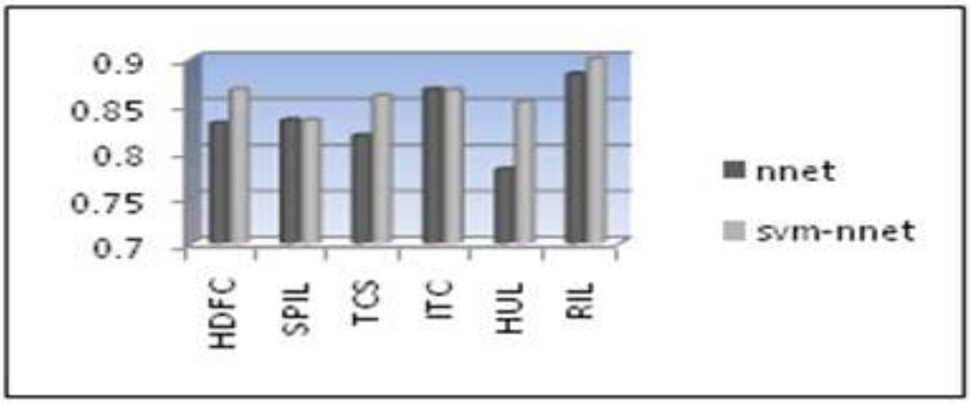

Figure 3: Evaluation Measure Accuracy

Among six companies accuracy of HUL increases from 78% to 85% and there is no difference in accuracy for SPIL, but AUC value increase from 88% to 93%. Table 3 shows the comparative results before and after SVM feature selection. It is very evident that accuracy increases from 1% to 7% after feature selection using SVM.

Apart from predictive accuracy, other evaluation measures F-measure, AUC [7] value before and after feature selection is also computed and shown in table 2. The ROC curve is plotted for six companies before and after feature selection is depicted in Fig. 4. Based on ROC curve, further we confirmed that the SVM based feature selection technique enhanced the performance of the ANN prediction model.

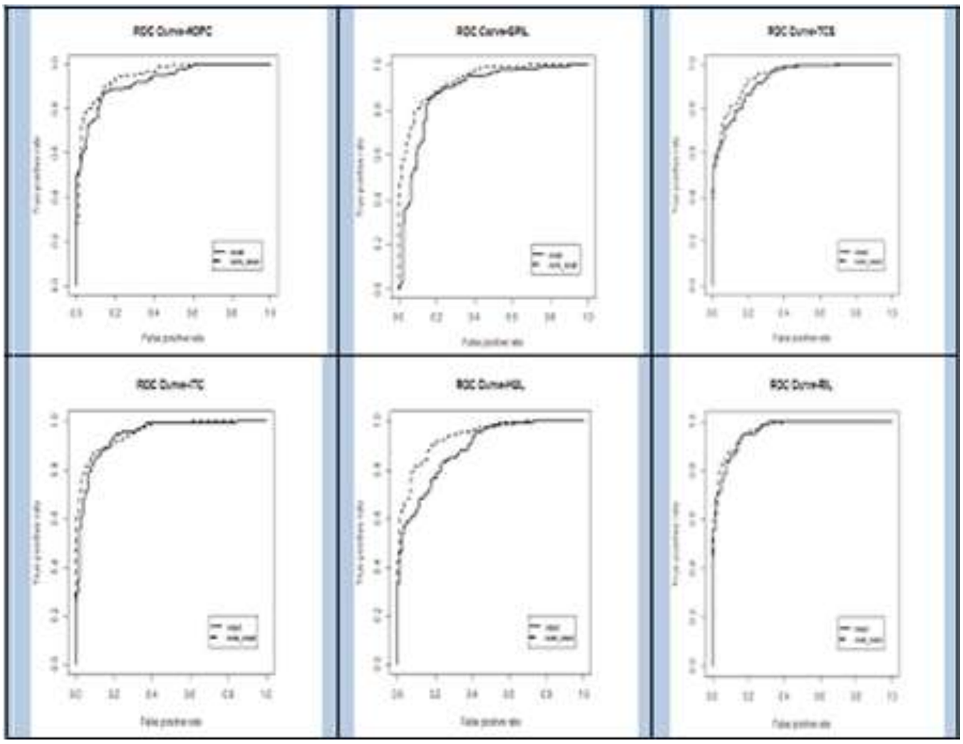

Figure 4: ROC curve for six companies

V. CONCLUSIONS

In this paper we described the application of a hybrid model in stock trend forecasting of six major capitalization companies of NSE using Artificial neural networks and Support Vector Machine. The theory behind ANN and SVM and its salient features are described in this study. In this study SVM is introduced to remove irrelevant, redundant and noisy features. After feature selection using SVM, classification is done using ANN. It is evident from the experimental results that feature selection using SVM improved the classification performance of ANN. Prediction accuracy of classification using a combination of SVM and ANN is between 83% and 90% as shown in Fig. 3. Thus, this hybrid model can be used for stock trend prediction in order to increase trader's investment returns.

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