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Market Timing Decisions by Hybrid Machine Learning Technique: A Case Study for Dhaka Stock Market

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Abstract

Stock market prediction has been a challenging task due to the nature of the data which is very noisy and time varying. However, this theory has been faced by many empirical studies and a number of researchers have successfully applied machine learning approaches to predict stock market. The problem studied here is about stock prediction for the use of investors. It is true investors usually get loss because of unclear investment objective and blind investment. This paper proposes to investigate the rough set model, the artificial neural network model and the hybrid artificial neural network model and the rough set model for determining the optimal buy and sell of a share on a Dhaka stock exchange. Confusion matrix is used to evaluate the performance of the observed and

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predicted classes for selected models. Our experimental result shows that the proposed hybrid model has higher accuracy than the single rough set model and the artificial neural network model. We believe this paper will be useful to stock investors to determine the optimal buy and sell time on Dhaka Stock Exchange.

Mathematics Subject Classification: 03Bxx:1, 03Cxx:1, 05Dxx:1

Keywords: Rough set, Neural network, Hybrid machine learning, Technical indicators, Stock market prediction, Confusion matrix

1 Introduction

People tend to invest in share market because of its high returns over time. In major financial markets around the world, trading in the share market has gained amazing popularity as a way of life to obtain huge profits. Therefore, any knowledge of future information regarding the price behavior of a particular share will absolutely ensure large profits in the market. Thus, appropriate prediction of a market is an essential factor for investors, buyers, sellers, fund managers, policy makers and others who are involved in this market. But in practice share market prediction has been a difficult task because this market is highly affected by many interrelated economic, political and even psychological causes. These causes interact with each other in a complex manner, therefore, it is difficult to predict the movements of a share market. However, analysis and prediction in share market has been a hot research for many years (e.g. [1-5] and others).

Generally, in share market the methods used to make investment decisions fall into two categories:

(i) fundamental analysis

(ii) technical analysis. Fundamental analysis is a complete method involving in-depth analysis of the company's annual report and indicators of the general economy. It requires real and reliable information of a company's financial report, competitive strength and economic conditions. This method assumes that current price depends on its essential value and anticipated return on investment and new information about a company that will affect the movement of its share price. On the other hand, technical analysis only considers the actual history of trading and price in a stock. The underlying theory of this analysis is based on an assumption that the market price reflects all known information about individual stock. It is known that in predicting market movement, approximately 90% of stock traders use this method in their investment analysis. This is basically the psychological analysis of market participants and is mostly concerned with market indicators. These indicators look at the trend of price indices and individual stocks evaluating the current position of the stock. The theory underlying these indicators is that once a trend is in motion, it will continue in that direction. Technical indicators such as the moving average (MA), trading bands, Bollinger bands, volume, moving average convergence/divergence (MACD), relative strength index (RSI), price rate of change (PROC) and others have been widely used to analyze the trend of market direction via chart presentations.

To maximize profit from the share market, more and more best forecasting techniques are used by different analyzers. Nowadays, analyzers are no longer relying on a single technique to provide information about the future of the markets but rather use a variety of techniques to obtain reliable outputs. This paper describes the invention about the share market prediction using data mining approaches. Data mining is a computational intelligence discipline that contributes tools for data analysis, discovery of new knowledge and autonomous decision making. In recent years ([5-6] and others), many researches in share market prediction are conducted using computational intelligence methods and have shown superior prediction results. Such computational intelligence methods involve artificial neural network (ANN), genetic algorithm, rough set theory (RST), fuzzy logic, ant colony method, bee colony method and others. The focus of the paper is to predict Dhaka share market movements using the popular and recently used model based on rough set and neural network approaches. The problem studied here is about the stock prediction for investors' usage. We have chosen the neural network approach of superior ability of knowledge discovery and the rough set approach for powerful rules extraction abilities. We wish to extract knowledge in the form of rules from the daily Dhaka stock movements that would guide investors, buyers, sellers and others whether to buy, sell or hold a share. We used most important technical indicators to create rough set model and ANN model.

The paper is organized as follows: Section 2 discusses the proposed prediction models. A brief description about technical indicators is explained in Section 3. Experimentation is covered in section 4 including data preparation, analysis, results and discussion of the results and finally conclusions are provided in section 5.

2 Prediction Models

RS and ANN have both been employed in stock market prediction [1-2, 5]. Based on previous researches, both methods have shown in capability in this application. ANN has been used to predict the stock market for the past few years [9,11] and is still being investigation many researches with the objective of achieving higher and accurate prediction. Like ANN, RS has also shown successful results with better accuracy [2,6,10]. Many RS models have been developed for different areas including many applications including financial and investment areas [1], forecasting [12], feature selection [13-14], analysis of share market data [1-5] and many others. A detailed review of applications of RST in financial domain can be found in [6]. Based on the successful results in applied literature given by RS and ANN in stock market prediction, we have chosen the following models to predict Dhaka share market. These are (i) Model based on RS

(ii) model based on ANN and (iii) hybrid model ANN and RS. A brief description about the above models is described in the following section.

2.1 Rough set predictions model (RSPM)

RS was introduced by Pawlak [7]. It is developed based on mathematical tool to deal with vagueness and uncertainty in the classification of objects in a set. In rough sets, data is organized in a table called decision table, containing attributes as columns and data elements as rows. The class label is called as decision attribute. The rest of the attributes are the condition attributes. For rows, RST employs the notion of indiscernible class, while for columns it employs the notion of indiscernible attribute to identify significant attributes. The key idea of this approach lies in the analysis of limits of discernibility. RST defines three regions based on the equivalent classes induces by the attribute values: lower approximation, upper approximation and boundary. The lower approximation concerns of all objects which definitely belong to the set. The upper approximation consist all objects which probably belong to the set. The boundary is the difference between the upper approximation and the lower approximation. Based on the concept of indiscernibility relation, redundant features can be identified and eliminated to reduce the number of features. Thus, RST is suitable for data reduction and very useful as a preprocessing tool. The advantage of rough set is that it does not need any preliminary (or additional) information about data, e.g. probability distribution of data, grade of membership like fuzzy set theory (details see [7]).

Analysis of the data by RS can be divided into 5 steps: Construct information table, identify indiscernibility relations, finding reducts, generation rules and finally classification. An information table is in the form of rows and columns represent the original data. The set of indiscernibility relations based on the information table are derived using objects with the set of features. The upper and lower approximations are used to deal with inconsistent objects that probably or definitely belong to the set. The main concern of RST is to find the smallest subset (known as reducts, computed by discernibility matrix) of features without losing any information. Reducts are the sets that contain the same quality of sorting whole original set of features but posses the least features. From the reducts, production rules to classify the objects are generated by the logical statements of the type IF-THEN condition. The decision rules are measured by support, length, coverage and accuracy. The rule support is the number of records that fully exhibit the property described by the IF-THEN condition. The length is defined as the number of conditional elements of the IF part. The coverage is defined as the proportion of records that are identified by the IF or THEN parts. The accuracy measures the reliability of the rule in the THEN parts. If coverage is 1 for a rule, then this rule is known as complete it means that any objects belonging to the class while deterministic rules are rules with accuracy equal to 1. The rules are correct with both coverage and accuracy equal to 1. For a detailed description of RS, see [7].

2.2 ANN prediction model

It is introduced by Culloch [8]. It is a technique that is developed by simulating the biological nervous systems such as the human brain. It consist the following processing functions:

(i) receiving inputs
(ii) assigning appropriate weight coefficient of inputs
(iii) calculating weighted sum of inputs
(iv) comparing this sum with some threshold and finally
(v) determining an appropriate output value.

Figure 1 presents a basic structure of ANN, which has 1 input layer, two hidden layers (with sufficient no. of neurons) and 1 output layer. Thus, each neuron receives an input P_{Rx1}, which is multiplied by weights W_{NxR} and bias b_{Nx1} to produce the net input as n = WP+b, where R are the number of elements in input vector and N are the no. of neurons in the hidden layers. Passing net input through an activation function produces the output of the neurons. Usually, the sigmoid function [$y=f(x)=1/(1+e^{-x})$] is used as the activation function. The properties of this function need to mimic the nerve cell which either fires or does not fire.

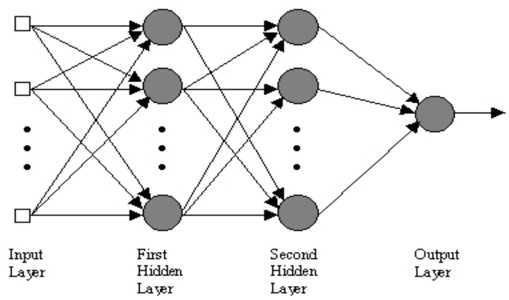

Figure 1: An ANN network

Other used activation functions are hard limiter, pureline, transig, logsigmoid and others. Networks are trained so that a particular input leads to a specific target output. The training algorithm is the standard black propagation (BP), which uses the gradient descent (GD) technique to minimize error over all training data. During training, each desired output is compared with the actual output and calculates error at the output layer. The backward pass is the error BP and adjustments of weights. Thus, the network is adjusted based on a comparison of the output and the target until the network output matches the target. After the training process is completed, the network with specified weights can be used for testing a set of data different than those for training. For details, see [8].

3 Technical Indicators

Technical analysis relies heavily on the availability of historical data. Investment managers calculate different indicators from available data and plot them as charts to predict the future. Observations of price, direction, and volume on the charts assist managers in making decisions on their investment portfolios. The following most widely used indicators were used in this study: MACD, moving average over a 5-days period (MA5), moving average over a 12-day period (MA12), PROC and RSI. A very brief description about the considered indicators with interpretation is described as follows:

3.1 MACD

It is an oscillator function used by technical analysts to spot overbought and oversold conditions. MACD is calculated by subtracting the value of a 26-period exponential moving average from a 12-period exponential moving average.

$$MACD = EMA(Index, 12)-EMA(index, 26)$$

where EMA is the exponential moving average and SMA is the simple moving average. As its name implies, MACD is all about the convergence and divergence of the two moving averages. Convergence occurs when the moving averages move towards each other. Divergence occurs when the moving averages move away from each other. The shorter moving average (12-day) is faster and responsible for most MACD movements. The longer moving average (26-day) is slower and less reactive to price changes in the underlying stock.

3.2 MA5

It is the 5-day moving average and is calculated by the last 5 indexes are added together and then divided by 5.

3.3 MA12

MA12 is the 12-day moving average and is calculated by the last 12 indexes are added together and then divided by 12. Note that by MA, a trader is able to understand the strength of the long-term trend of the prices.

3.4 PROC

PROC attribute is a price momentum indicator. It is calculated by the following formula:

(today's index – index n periods ago) / index n periods ago

If the stock's price is higher (lower) today than n periods ago, PROC will be a positive (negative) number. As the security's price increases (decreases), its PROC will rise (fall). The faster prices rise or fall, the faster PROC will rise or fall. Thus, PROC values indicate an overall picture of trend strength generation.

3.5 RSI

One of the most popular technical analysis indicators, RSI (developed by Wilder [15] is an oscillator that measures current price strength in relation to previous prices. It is calculated as the ratio of two exponentially smoothed MA. Mathematically it is defined as

$$RSI = 100-(100(1+R)),\ 0<RSI<100$$

where R = AG/AL, AG is the average price gain over some period and AL is the average price drop over some period. The name RSI indicates internal strength of price. RSI is used to generate buy and sell signals. It also show overbought and oversold conditions that confirm price movement and warn of potential price reversals through divergences. If we choose (for example) two references lines at 30 and 70 and if we observe RSI dips below the 30 line, a buy signal is generated. Likewise, if RSI exceeds the 70 line, a sell signal is generated.

Table 1: Daily stock price movement

Date	Total Trade	Total Volume	Total value in Taka(mn)	Total Market Cap. In Taka (mn)	DSE General Index
06/07/12	79537	56802386	2989.670	2551077.1	4769.394
06/10/12	36858	27487186	1363.139	2532069.0	4725.725
06/11/12	44550	34578322	1564.310	2517980.5	4689.201
06/12/12	41760	29559249	1287.442	2547020.2	4691.297
06/13/12	51959	36631286	1496.727	2516529.1	4680.616

The above indicators are used as dependent attributes in our analysis. The decision attribute is the trend of the stock market and can be used to make decisions.

4 Case Study: Dhaka Stock Price Index

To test and verify the prediction capability of the RS model, the ANN model and the hybrid ANN_RS model, the daily stock movement of all stocks traded in Dhaka Stock Exchange and spanning over a period of 8 years (Jan 2004- June 2012) were captured.

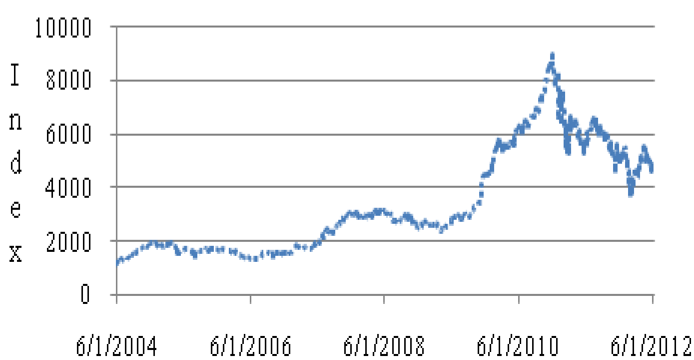

Figure 2: Time plots of the index

Table 1 represents a sample of the stock's daily movements and Figure 2 shows stock's movements with respect to time. We can observe that there has an increasing trend of the prices up to April 2010. Then there is a (looks like) crash in market observed after that. Obviously there have reasons those could be economic, political and/or psychological. Details, see http://www.dse.com.bd.

Statistics characteristics of the selected stock index are analyzed first before applying it to the selected forecasting models. Table 2 shown numerical measures for selected periods. In Table 3 we have presented selected attributes (MACD, MA5, MA12, PROC and RSI) used in the creation of rough set decision table and inputs to the ANN model. These attributes are calculated from the DSE general index. We have chosen these indicators because it is well known that technical analysts usually use these indicators to predict the movements of stocks. The decision attribute D in the Table 3 indicates the future direction of the data set and is constructed using the following formula:

$$D = \frac{\sum_{i=1}^{n}((n+1)-i)\,sign[\text{index}(i)-\text{index}(0)]}{\sum_{i=1}^{n} i}$$

where index(0) is today's index and index(i) is the ith index in the future. The above equation specifies a range -1 to +1 for D. A value of +1 indicate that the next day's price is higher than that of the current date, -1 indicate that the next day's price is lower than that of the current date and 0 indicate no change. From the original data we performed data preparation tasks that resulted in a new information table with conditional attributes A = (MACD, MA5, MA12, PROC, RSI) and a decision attribute D and it is presented in Table 3.

Table 2: Numerical summary of DSE

Min	Mean	Max	Variance	Stdev	Skew	Kurt
1.185e+003	3.350e+003	8.918e+003	3.680e+006	1.9186e+003	0.8699	2.5589

Table 3: Sample of the data after post processing

Date	Total Trade	Total Volume	Total Value in Tk(mn)	Total Market Cap. in Tk(mn)	DSE General Index	MACD	MA5 (1000)	MA12 (1000)	PROC	RSI	D
6/3/2012	79024	52834504	2773.02	2582225.4	4855.36	-97.68	4.71	4.82	-3.694	36.57	-1
6/4/2012	98570	64218144	3279.275	2509830.4	4675.98	-101.5	4.72	4.79	1.410	30.74	1
6/5/2012	59303	38597358	1956.071	2537026.4	4741.94	-98.23	4.74	4.77	1.055	35.86	1
6/6/2012	72496	62699058	3079.895	2557495.7	4791.98	-90.49	4.76	4.75	-0.471	39.82	-1
6/7/2012	79537	56802386	2989.67	2551077.1	4769.39	-85.19	4.77	4.74	-0.916	39.69	-1
6/10/2012	36858	27487186	1363.139	2532069	4725.73	-83.56	4.74	4.73	-0.773	34.80	-1

4.1 RS and ANN model building

In this section, we will create rough set model, ANN model and hybrid model of ANN and RS (ANN_RS) based on considered technical indicators. The ANN_RS hybridizes high generality of ANN and rules extraction ability of rough set theory. Data are divided into 2 parts: training and testing sets. The training set contains 70% of the collected data and the testing set contains the rest of data.

4.2 Evaluation methods

Confusion matrix is used to evaluate the performance of the observed and predicted classes for selected models. This matrix is a table summarizing the number of true positive (TP) class, false positive (FP) class, false negative (FN) class and true negative (TN) class. For example, TP means the output of the prediction model is rise and also the stock price actually rises and so on.

4.3 Prediction model – the rough set model

The process of stock market data prediction and analysis is depicted in the following steps:

- Generate efficient indicators based on data
- Choose the training data set and test data set
- Put into rough sets model
- Extract trading rules
- Implement in the real market

The rough set analysis of the data involved computation of reducts from data, derivation of rules from reducts, rule evaluation and prediction processes. The Rosetta Rough Set Toolkit was used to perform reducts and generate decision rules. The reducts that were generated from our selected data are shown in Table 4.

We used the Johnhon's reducer algorithm and the equal binning decretized method. Table 5 shows a partial set of the generated rules. These obtained rules are used to build the prediction systems. From our selected data we obtained a set of 12 reducts. The following is an example of a rule obtained from a reduct 1 in Table 4.

IF-THEN Rule:

IF MACD([-5.336, 30.555)) and MA5([*, 1885.2000)) and PROC([-0.3425, 0.6405))

THEN Decision class (-1) OR (1)

Training data

Support (LHS) = 192

Coverage (LHS) = 0.202531645

Accuracy (RHS) = 0.614583333

Table 4: Reducts generated

Reduct #	Reduct
1	{MACD, MA5, PROC}
2	{PROC}
3	{PROC, RSI}
4	{MACD, MA5, MA12, PROC}
5	{MA12, PROC, RSI}
6	{MA5, MA12, PROC}
7	{MACD, PROC, RSI}
8	{MA5, PROC, RSI}
9	{MACD, MA5, RSI}
10	{MA5, MA12}
11	{MACD, MA12, PROC, RSI}
12	{MACD, MA5, PROC, RSI}

The rule has three conditional attributes corresponding to the IF part. The rule has a decision of -1 or 1. From this rule we can see that the conditional attributes have a support of 192 objects from a total of 948 objects. Of those 192 objects, 118 objects (61%) have a decision value of -1 or 1. We are looking for rules with relatively high support and high accuracy. Once rules where obtained, the testing (see below for an example) of each rule ensured that the knowledge was correct.

Testing data

Support (LHS) = 189

Coverage (LHS) = 0.199367088

Accuracy (RHS) = 0.687830687

Each rule fired against the testing set to confirm support, accuracy and confidence measures. Comparison between measures obtained by firing the rules against the training and testing data is needed to make certain that the knowledge is a correct depiction of the original data. The confusion matrix for the RS model is provided in Table 5. On average the RS model provides 72.31% prediction accuracy of falling stock prices, 80.80% prediction accuracy of rising stock prices and overall 87% prediction accuracy. Therefore we can say that this model is 72% useful to predict falling stock and 87% useful to predict rising stock.

Table 5: Confusion matrix for the RS model

	Predicted		
Actual	Fall (-1)	Rise (+1)	Accuracy(%)
Fall (-1)	316	121	0.723112
Rise (+1)	1	510	1.0
Accuracy(%)	1.0	0.808241	0.872228

4.4 Prediction Model –The ANN Model

An ANN topology of 9:15:18:1, learning rate 0.01, momentum factor parameter 0.90 is selected using the error and trial method. We used the sigmoid transfer function at input and output layers and trained the network by the Levenberg Marquardt back-propagation algorithm. The learning rate parameter controls the step size in each iteration and the momentum parameter avoids getting stuck. The inputs to the ANN model are $index_t$, $index_{t-i}$ (i =1,2,3,….p, p is the AR order), MACD, MA5, MA12, PROC, RSI and the output $index_{t+1}$. We have selected lag order using the Akaike Information Criteria (AIC). Others criteria such as BIC, SIC and others can also be used. The confusion matrix is provided in Table 6.

Table 6: Confusion matrix for the ANN model

	Predicted		Accuracy (%)
Actual	Fall (-1)	Rise(+1)	
Fall (-1)	290	108	0.728643
Rise (+1)	97	453	0.823636
Accuracy (%)	0.749354	0.807486	0.783755

On average, the ANN model provides 72.86% prediction accuracy of falling stock prices, 80.74% prediction accuracy of rising stock prices and overall 78.37% prediction accuracy. This is interesting to see that although this model performs better than the RST model to predict falling stock prices, but it performs poorly for overall prediction. The reason the rate prediction for the class of FN is higher as compare to the RST model.

4.5 Model combinations – the ANN_RS model

Under the sections 4.3 and 4.4 the RS and the ANN models are constructed individually as the baselines, then these two models are combined to enhance the rate of prediction accuracy. First, an ANN topology of 9:12:14:1, learning rate 0.01, momentum factor parameter 0.95 is chosen using the error and trial method. Then the Rosetta Rough Set Toolkit was used to perform reducts and generate decision rules based on the predicted index. To see the performance of the model, the confusion matrix is summarized in the Table 7. After developing the two different baseline models, we found that the RS model provides better performances than the ANN model. The hybrid model ANN_RS provides the 95.93% prediction accuracy of falling stock prices, 96.87% prediction accuracy of rising stock prices and overall 97.89% prediction accuracy.

From the comparison among the models RS, ANN and hybrid ANN_RS, we can discover that the hybrid ANN_RS model has better forecasting performances than others. That means this model has better average prediction accuracy. Therefore, according to our study among three considered forecasting models, the hybrid model can be recommended to predict the daily Dhaka stock movements that would guide investors, buyers, sellers and others when to buy, sell or hold a share.

Table 7: Confusion matrix for the ANN_RS model

	Predicted		Accuracy (%)
Actual	Fall (-1)	Rise (+1)	
Fall (-1)	401	17	0.959330
Rise (+1)	3	527	0.994339
Accuracy (%)	0.992574	0.96875	0.978902

5 Conclusion

This paper presents an idea of using hybrid machine learning techniques to determine the optimal buy and sell time on Dhaka Stock Exchange. We combined the ANN forecasting model and the rough set forecasting model to enhance the rate of prediction accuracy as well as to provide decision rules whether to buy, sell or hold a stock. We have chosen the neural network approach of superior ability of knowledge discovery and the rough set approach for powerful rules extraction abilities. The results of this proposed hybrid models are compared for the baseline rough set model and ANN model. To increase the efficiency of the prediction process, the rough set equal binning discretized method is used to discretize the data. Rough set Johnson's reducer algorithm is then applied to find all reducts of the data which contains the minimal subset of attributes. We used the Levenberg Marquardt back-propagation algorithm to train the ANN network. Confusion matrix is used to evaluate the performance of the selected models and classes (fall and rise). The experimental result shows our proposed hybrid model has 97% accuracy which is higher than the single rough set forecasting model and the ANN forecasting model. For future work the following issues could be considered. Other forecasting techniques such as genetic algorithm, neuro ANN model etc. can be applied for further comparisons. To obtain better prediction, other advanced reduction techniques such as genetic algorithm, Holte's algorithm can be applied.

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