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FORECASTING STOCK MARKET TRENDS BY LOGISTIC REGRESSION AND NEURAL NETWORKS

EVIDENCE FROM KSA STOCK MARKET

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Abstract

Estimating stock market trends is very important for investors to act for future. Kingdom of Saudi Arabia (KSA) stock market is evolving rapidly; so the objective of this paper is to forecast the stock market trends using logistic model and artificial neural network. Logistic model is a variety of probabilistic statistical classification model. It is also used to predict a binary response from a binary predictor. Artificial neural networks are used for forecasting because of their capabilities of pattern recognition and machine learning. Both methods are used to forecast the stock prices of upcoming period. The model has used the preprocessed data set of closing value of TASA Index. The data set encompassed the trading days from 5th April, 2007 to 1st January, 2015. With logistic regression it may be observed that four variables i.e. open price, higher price, lower price and oil can classify up to 81.55% into two categories up and down. While with neural networks The prediction accuracy of the model is high both for the training data (84.12%) and test data (81.84%).

Keywords: Forecasting, Logistic Model, Neural Networks, Stock Index, Trends

INTRODUCTION

Recently predicting stock market trends is gaining more consideration, perhaps because of the fact that if the trend of the market is successfully forecasted the traders may be well directed. The profitability of trading in the stock market to a large extent rest on the predictability. More over the forecast trends of the market will support the regulators of the market in taking corrective measures.

Estimating in stock market has been constructed on traditional statistical forecast methods for long time. Linear models have been the midpoint of such traditional methods. But, these methods have seldom demonstrated successful due to the existence of noise and non-linearity in historical data. The successful use of nonlinear methods in other arenas of investigation has flashed the optimisms of financials. Non linear methods propose an advanced approach of perceiving stock prices, and it offers novel methods for practically assessing their nature.

The objective of this paper is to forecast the stock market trends using logistic model and artificial neural network. Logistic model is a variety of probabilistic statistical classification model. It is also used to predict a binary response from a binary predictor. Artificial neural networks are used for forecasting because of their capabilities of pattern recognition and machine learning. Both methods are used to forecast the stock prices of upcoming period. The model has used the preprocessed data set of closing value of TASA Index. The data set encompassed the trading days from 5thApril, 2007 to 1st January; 2015.Both methods give us estimation with up to 80% accuracy.

This paper is structured in four sections. The first one introduce the study, in the second we review literature linked to our paper, then we explain methodology of research and present results, the forth section concludes the paper.

LITERATURE REVIEW

Logistic Regression is a multivariate analysis model (Lee, 2004) very useful for prediction. The applications of this model in the area of finance are growing rapidly. Many researchers employed the multivariate discriminant analysis prediction model. Altman is the pioneer in the year 1968 while logistic regression was used by the Ohlson in 1980. The first study on prediction focuses on classifying companies as either non-defaulters or defaulters.

In forecasting bankruptcy and financial distress, logistic regression was applied by Ohlson (1980) and then by Zavgren (1985) and other researchers. Logistic regression technique yields coefficients for each independent variable based on a sample of data (Huang, Chai and Peng, 2007). Logistic regression models with more than one explanatory variable are applied in practice (Haines and others, 2007, Pardo, Pardo and Pardo, 2005). The benefit of logistic regression is that variables may be either discrete or continuous; they do not necessarily have normal distributions (Lee, 2004).

Neural networks have showed to be a talented area of investigation in the field of finance. Neural network practices in finance comprise assessing the risk of mortgage loans (Collins, Ghosh and Scofield, 1988), scoring the value of company bonds (Dutta & Shekhar, 1988), forecasting financial default (Altman, et.al., 1994), ranking of credit card users (Suan & Chye, 1997) and expecting bond ratings (Hatfield & White, 1996). Neural networks are also applied in areas such as valuing of derivatives (Hutchinson, 1994, Refenes, 1997, McCluskey, 1993), etc.

Actually, numerous practitioners in the stock market have also understood the likely of neural networks. Hadavandi, Shavandi et al. (2010) show an combined approach founded on artificial neural networks (ANN) and genetic fuzzy systems (GFS) for building a stock price predicting expert system. Kara, Acar Boyacioglu et al (2010) used artificial neural networks and support vector machines in expecting direction of stock price index of the Istanbul Stock Exchange. Shen, Guo et al. (2010) employed a radial basis function neural network and the artificial fish swarm algorithm (AFSA) to estimate the stock indices of the Shanghai Stock Exchange.

Additionally, Chih-Fong and Yu-Chieh (2010) jointed multiple feature assortment methods to recognize more representative variables for improved forecast for investors. In particular, they used: Genetic Algorithms (GA), Principal Component Analysis (PCA) and decision trees (CART). Esfahanipour and Aghamiri (2010) developed Neuro-Fuzzy Inference System implemented on a Takagi–Sugeno–Kang (TSK) for stock price prediction.

Also, Ni, Ni et al (2011) hybridizes fractal feature selection method and support vector machine to predict the direction of daily stock price index. Bajestani and Zare (2011) offered a new method to predict TAIEX based on a high-order type 2 fuzzy time series. The results designated that the proposed model beats previous studies.

RESEARCH METHODOLOGY

The data consists of daily index values of the Saudi stock market (TASA). The period under consideration is 05/04/2008to 01/01/2015. The data set consists of 1342 data points. The data has been obtained from the official web site of Saudi stock market that provides daily stock market data. The entire analysis has been done basically on the daily returns of the stock market index TASA.

Application of Logistic Regression

Logistic regression is used in our study because we assume that the relation between variables is non-linear. Also this type of regression is preferred when the response variable is binary which means that can take only two values 1 or 0.

Logistic regression could forecast the likelihood, or the odds ratio, of the outcome based on the predictor variables, or covariates. The significance of logistic regression can be evaluated by the log likelihood test, given as the model chi-square test, evaluated at the $p < 0.05$ level, or the Wald statistic. Logistic regression has the advantage of being less affected than discriminant analysis when the normality of the variable cannot be assumed.

It has the capacity to analyze a mix of all types of predictors [Hair, 1995]. Logistic regression, which assumes the errors are drawn from a binomial distribution, is formulated to predict and explain a binary categorical variable instead of a metric measure. In logistic regression, the dependent variable is a log odd or logit, which is the natural log of the odds.

In the logistic regression model, the relationship between Z and the probability of the event of interest is described by this link function.

$$p_i = \frac{e^{zi}}{1+e^{zi}} = \frac{1}{1+e^{-zi}}$$

$z_i = log(p_i/1 - p_i)$

Where

p_i is the probability the i^{th} case experiences the event of interest

z_i is the value of the unobserved continuous variable for the i^{th} case

The z value is the odds ratio. It is expressed by

$$z_i = c + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_p x_{ip}$$

Where

x_{ij} is the j^{th} predictor for the i^{th} case

β_j is the j^{th} coefficient

P is the number of predictors

βs are the regression coefficients that are estimated through an iterative maximum likelihood method. However, because of the subjectivity of the choice of these misclassification costs in practice, most researchers minimize the total error rate and, hence, implicitly assume equal costs of type I and type II errors [Ohlson, 1980; Zavgren, 1985].

In order to carry out logistic regression analysis, first a method is needed for classifying returns as a “1” or “0” for a given day. In this study we use a method that is simple and objective, if the value of a return in day j is above the return in day j-1, it is noted as a “1”; otherwise, it is classified as a “0”.

The return was calculated using the following formula:

$$return = \frac{p_j - p_{j-1}}{p_{j-1}} \times 100$$

Where:

p_j is the closing price for day j

p_{j-1} is the closing price for day j-1

As mentioned, the study contains 1678 data where 1342 are used for estimating and 336 used for validating the model. For variables we have the market return as dependent variable and five independent variables. One of them is fundamental variable oil, and the reminders are technical variables: open price, higher price, lower price and turnover.

We conduct the logistic regression in two steps. The first called general model where we introduced all our independent variables. The second is called the reduced model where we use only the significant variables of the general model. The estimation is done using the software Eviews 7.

ANALYSIS AND FINDINGS

Table 1: General Model Results

Variables	Coefficient	Std. error	z-statistic	Prob.
Constant	0.178794	0.076468	2.338142	0.0194
Higher price	186.6705	17.63165	10.58724	0.0000
Lower price	191.2550	14.72109	12.99190	0.0000
Oil	9.394324	3.596176	2.612309	0.0090
Open price	-189.6573	13.24681	-14.31721	0.0000
Turnover	0.854115	0.492648	1.733722	0.0830*

(*): is significantly non-significant at 5% level

The final logistic regression equation is estimated in general model by using the maximum likelihood estimation:

Z = 0.178794 + 186.6705 * **Higher** + 191.2550 * **Lower** + 9.394324 * **Oil** - 189.6573 * **Open** + 0.854115 * **Turnover**

Where,

Z = log (p /1 – p)

and ‘p’ is the probability that the variable is 1.

We note that the statistic LR is equal to 716.5421. This statistic suppose in the null hypothesis that all coefficients are equal to zero except the constant. Here we reject this hypothesis with zero probability to be wrong. This means that our model is globally significant. To enforce the results of the LR test we make the wald test which study the same hypothesis. We found F-statistics equal to 57.49 (prob =0) and chi-square equal to 287.48 (prob=0). So we reject the null hypothesis.

Also we have McFadden R-squared equal to 0.387 which is between 0.2 and 0.4 and that means the explicative power of the model is excellent.

Regarding the results of this model, the variable lower price has the higher influence on the market return and is more important in prediction among the technical variables chose in our estimation while the variable turnover is significantly non-significant so it will be removed in the next step which is the reduced model.

Table 2: Reduced Model Results

Variables	Coefficient	Std. error	z-statistic	Prob.
Constant	0.173331	0.076299	2.271736	0.0231
Higher price	196.5624	16.86996	11.65162	0.0000
Lower price	187.9323	14.57554	12.89367	0.0000
Oil	9.484048	3.582098	2.647623	0.0081
Open price	-191.7596	13.23194	-14.49217	0.0000

The final logistic regression equation is estimated in a reduced model by using the maximum likelihood estimation:

Z = 0.173331 + 196.5624 * **Higher** + 187.9323 * **Lower** + 9.484048 * **Oil** - 191.7596 * **Open**

Where

Z = log (p /1 – p)

and ‘p’ is the probability that the variable is 1.

In this estimation the higher price has more influence on the market return and can be more significant in forecasting stock return.

We note that the statistic LR is equal to 713.5310. This statistic suppose in the null hypothesis that all coefficients are equal to zero except the constant. Here we reject this hypothesis with zero probability to be wrong. This means that our model is globally significant. To enforce the results of the LR test we make the Wald test which study the same hypothesis. We found F-statistics equal to 71.30506 (prob =0) and chi-square equal to 285.2202 (prob=0). So we reject the null hypothesis.

To measure the quality of our model we calculate McFadden Rsquare, Cox & Snell Rsquare, max Rsquare and Nagelkerke adjusted Rsquare. The results are:

Table 3: Measuring the Quality of Models

Measure	Complete model	Reduced model
McFadden Rsquare	0.3870	0.3854
Cox &Snell Rsquare	0.4136	0.4123
Max Rsquare	0.5707	0.5716
Nagelkerke adjusted Rsquare	0.7236	0.7212

These indicators show at first that the explicative power still the same after moving to the reduced model. Secondly, the Nagelkerke adjusted Rsquare is close to 1 which indicate that the significant power of our models is great.

We can also scan the information criteria that furnish a measure of the quality of information given by the model. We can find this criteria by a combination between the log likelihood, the number of observations and the number of variables. These criteria are: AKAIKE, Schwarz and Hannan-Quin.

Table 4: Measuring the Quality of Information Given by Models

Measure	Complete model	Reduced model
Akaike info criterion	0.854574	0.855328
Schwarz criterion	0.877832	0.874709
Hannan-Quinn citerions	0.863287	0.862588

We note from table (4) that the criteria is the same for Akaike while Schwarz and Hannan-Quinn decreased in the reduced model which means that the later give better information.

The last step to validate the reduced model is to check its predictive quality. For this reason, we will make the test of Goodness-of-Fit Evaluation for Binary Specification: Andrews and Hosmer-Lemeshow Tests. The results are:

Table 5: Measuring the Predictive Quality of Models

Measure	Complete model	Reduced model
H-L Statistic	111.0267	112.9785
Prob. Chi-Sq(8)	0.0000	0.0000
Andrews Statistic	65.3223	64.2026
Prob. Chi-Sq(10)	0.0000	0.0000

This test reflect that the reduced model give a better predictive quality with zero probability of error. So, we will estimate the value of y using the reduced model for our 1342 observation. The test of Expectation-Prediction Evaluation for Binary Specification shows the results as presented in the table 6.

Table 6: Expectation-Prediction Evaluation

Measure	Correct (%)	Wrong (%)
Y=1	86.50	13.50
Y=0	80.68	19.32
Total	**83.83**	**16.17**

With the reduced model, 83.83% of estimation are correct. So we validate this model and we can now interpret the coefficient and make an estimation of the reminder data.

Here, we will speak about the marginal effect of variables. The marginal effect for jth explicative variable $x_i^{[j]}$is defined as :

$$\frac{\partial p_i}{\partial x_i^{[j]}} = f(x_i\beta).\beta_j = \frac{e^{x_i\beta}}{(1+e^{x_i\beta})^2}\beta_j$$

Because of the sign of $f(x_i\beta)$is always positive, so the sign of this derivate is the same of the coefficient. So the positive sign indicate an increase in the probability of y to be equal to 1 which is the case for variables: higher price, lower price, and oil. While a negative sign reflect a decrease in this probability which the case for the variable open price.

For more explanation we calculate the elasticity $\varepsilon_{p_i/x_i^{[j]}}$ as the variation in percentage of the probability p_i that $y_i = 1$ occurs due to a variation of 1% of the jth explicative variable $x_i^{[j]}$. Elasticity is defined as:

$$\forall i \in [1, N] \qquad \varepsilon_{p_i/x_i^{[j]}} = \frac{x_i^{[j]}\beta_j}{1+exp^{x_i\beta}}$$

Table 7: Elasticity of Variables in Complete Model

Variables	Higher price	Lower price	Oil	Open price
Elasticity	-1.04%	-0.93%	-0.021%	0.86%

If these variables change by 1% the occurrence probability of $y_i = 1$ decrease for all variables except the open price.

Using this result we will estimate the value of our dependent variable for the left 336 data in order to test the performance of our model. The results are shown in the following table:

Table 8: Testing the Performance of the Model

Prediction	Number	Percentage
Correct	274	81.55%
Wrong	62	18.45%
Total	336	100%

From the table above we can deduce that the accuracy of our model is of 81.55% which is very important and can help investor to implement the best investment strategy. 3-2- Application of artificial neural network

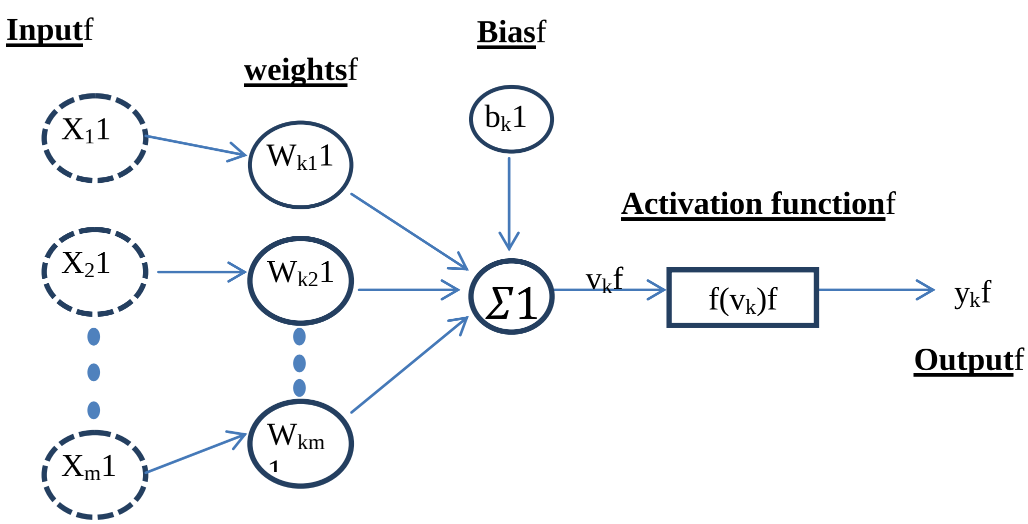
A neural network is a great data modeling device that is able to capture and represent complex input/output relations. The inspiration for the development of neural network technology stemmed from the wish to develop an artificial system that could make "intelligent" tasks similar to those done by the human brain. Neural networks resemble the human brain in the following two ways: At first, a neural network acquires knowledge through learning and secondly, a neural network's knowledge is stored within inter-neuron connection strengths known as synaptic weights.

From a very broad perspective, neural networks can be used for financial decision making in one of the three ways:

1. It can be provided with inputs, which enable it to find rules relating the current state of the system being predicted to future states.
2. It can have a window of inputs describing a fixed set of recent past states and relate those to future states.
3. It can be designed with an internal state to enable it to learn the relationship of an in definitely large set of past inputs to future states, which can be accomplished via recurrent connections.

In this paper, one model of neural network is selected among the main network architectures used in finance. The basis of the model is neuron structure as shown in Fig. 1.

Figure 1: Neuron model



These neurons act like parallel processing units. An artificial neuron is a unit that performs a simple mathematical operation on its inputs and imitates the functions of biological neurons and their unique process of learning. From Fig. 1 will have:

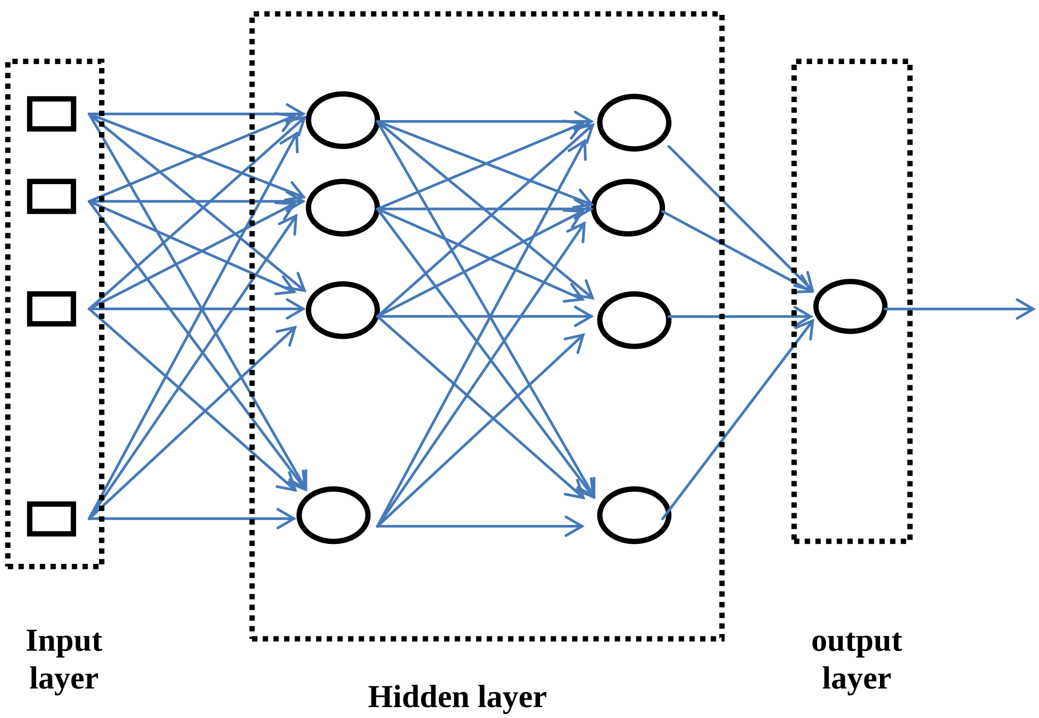
$$v_k = \sum_{j=1}^{m} x_j w_{kj} + b_k$$

The neuron output will be:

$$y_k = f(v_k)$$

Neural systems are naturally organized in layers. Layers are made up of a number of artificial neurons, which hold an activation function. Patterns are offered to the network via the input layer, which transfers to one, or more hidden layers where the actual processing is done through a system of fully or partially weighted connections. The hidden layers are then connected to an output layer where the response is output. Multilayer perceptron (MLP) is the most commonly used neural network with the back-Propagation Algorithm networks. This kind of neural networks is excellent at both prediction and classification. Using this neural network algorithm, both input and corresponding desired output data are given to the calibrating phase.

Figure 2: Neural Network Architecture



According to Wierenga and Kluytmans (1994) ANN can be proceeded in four steps:

Step 1

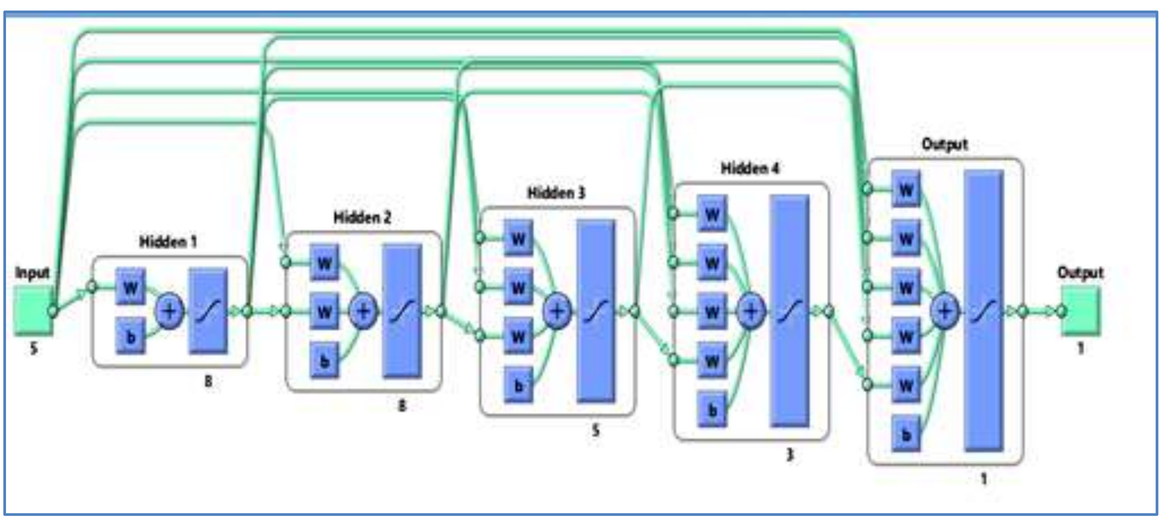
Set the number of input and output layers , the analyst must decide how many intermediate or hidden layers, the network offers only limited possibilities of adaptation, with one hidden layer is capable, with a sufficient number of neurons to approximate all continuous function (Hornik, 1991). A second hidden layer takes into account the discontinuities or detects relationships and interactions between variables. Indeed, in our study the use of hidden layers is very useful to detect all non-linear relationships between variables in the model. After several experimentations we used four (4) layers.

Step 2

Determine the number of neurons in layers. Each additional neuron allows taking into account specific profiles of input neurons. A more large number therefore allows better match the data presented but decreases capacity generalization of the network. Here again no general rule but empirical rules. The size of the hidden layer must be either equal to that of the input layer (Wierenga and Kluytmans , 1994) or is equal to 75% of the latter (Venugopal Baet, 1994) or is equal to the square root of the number of neurons in the input and output layer (Shepard,1990).

In our study we chose the approach of setting a maximum number of nodes in each hidden layer. Then, we eliminated those have no utility for the learning procedure. So the number of input nodes is equal to number of independent variables which is 5 (higher price, lower price, open price, oil and turnover). And the number of output nodes is equal to number of dependent variables which is 1 (index returns).

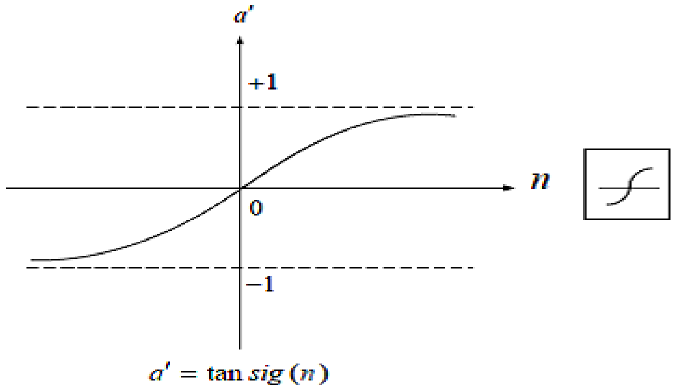
Figure 3: ANN structure



Step 3

Select the transfer function .because of the dependent variable is bounded [0,1], the logistic function is chosen for both hidden layers to the output layer(tansig)

Figure 4: Tan – sigmoid Transfer Function



Step 4

Choose learning. The retro-propagation algorithm requires determination of the adjustment parameter of the synaptic weight in each iteration. We have retained the learning method (trainrp) which is a network training function that updates weight and bias values according to the resilient back propagation algorithm (RPROP).

The assessment of the prediction performance of the different soft computing models was done with matlab 2013 by quantifying the prediction obtained on an independent data set. The mean absolute error (MAE) was used to study the performance of the trained forecasting models for the testing years. MAE is defined as follows:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left[P_{predicted\ \ i} - P_{actual\ \ i}\right]$$

Where:

$P_{predicted\ \ i}$is the predicted return on day i

$P_{actual\ \ i}$is actual return on day i

N is the number of observations

We used also Mean square error is used for evaluating the prediction accuracy of the model:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(P_{predicted\ \ i} - P_{actual\ \ i}\right)^2$$

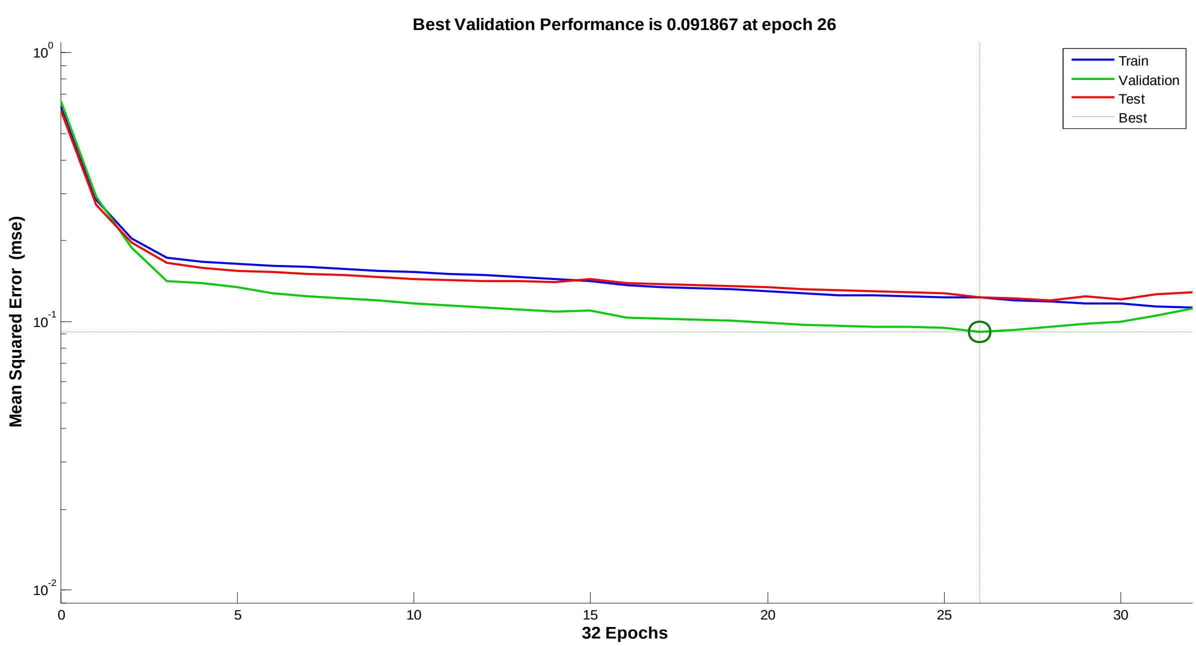
Table 9: ANN Structure

Neural network	MLP	Transfer function	Tan-sigmoid
Number of hidden layer	4	**Iterations**	70
Number of nodes in input layer	5	**Training pattern**	1342
Number of nodes in hidden layer 1	8	**Test pattern**	336
Number of nodes in hidden layer 2	8	**MAE (Training)**	0.2352
Number of nodes in hidden layer 3	5	**MSE (Training)**	0.1183
Number of nodes in hidden layer 4	3	**MAE (Prediction)**	0.2660
Number of nodes in output layer	1	**MSE (Prediction)**	0.1368

The network is trained by repeatedly presenting it with both the training and test data sets. To identify when to stop training, two parameters, namely the MAE and MSE of both the training and test sets were used. After 70 iterations, the MAE and MSE of the training set was 0.2352 and 0.1183 respectively, while those of test set was 0.2660 and 0.1368. The training was stopped after 70 iterations as there was no significant decrease in both parameters. Thus, any further training was not going to be productive or cause any significant changes. The prediction accuracy of the training data is 84.12% and that of test data is 81.84%.

From the result shown in Table 9, it is observed that the predicted values are in good agreement with exact values and the predicted error is very less. Also the results obtained clearly demonstrate that MLP method is reliable and accurate and effective for forecasting stock returns. Therefore the proposed ANN model with the developed structure shown in Table 9 can perform good prediction in stock market.

Figure 5: Mean Squared Errors



CONCLUSION

In this paper, an attempt is made to explore the use of logistic regression to determine the factors which significantly affect the evolution of the stock index. Logistic regression method helps the investor to form an opinion about the time to invest. It may be observed that four variables i.e. open price, higher price, lower price and oilcan classify up to 81.55% into two categories up and down. This prediction rate is very good, so it can be used for prediction with higher accuracy.

This study has also employed neural network to predict the direction of stock index return. Multi-layer perceptron network is trained using Tan-sigmoidal algorithm. The prediction accuracy of the model is high both for the training data (84.12%) and test data (81.84%).

We can deduce from this study that the use of logistic regression and neural network give us very close result. But, both methods give us a good result of prediction with very high accuracy using a mixture of fundamental and technical variables. So this study must be extended to use these methods in the prediction and classification of stock returns.

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