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Enhancing Prediction of NASDAQ Stock Market Based on Technical Indicators

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Abstract: The Stock Market (SM) prediction price is one of an interesting field at present because it is a chaotic, non-linear, dynamic, non-stationary, noisy and quite difficult. Data mining has been effectively used in stock predicting hence researchers have explored Technical Indicators (TIs) to optimize the parameters. The main objective of this study is to predict NASDAQ stock index values market using TIs and develop method of multilayer perceptron neural networks based on an Optimization Model (OMLP) which aims to reduce the error factor depending on the Jacobian vector and Hessian matrix according to the convergence factor reach to zero. 10-fold cross validation and 70% holdout testing methods are used to train data. Further, precision, recall, F1 measure, specificity, accuracy, root mean squared error and mean absolute error are considered as evaluation criteria. Finally, a comparison has been implemented on input features with and without TIs. The results show using TIs satisfy better results of prediction. The accuracy rate is raised from 55.3% of standard features only to 79.97% of proposed approach which depends on TIs.

Key words: Stock market prediction, developed multilayer perceptron neural network, optimization, technical Indicators, NASDAQ, accuracy

INTRODUCTION

Technical analysis has been used effectively on predicting accuracy of stock price movement. SM analysis is a broad area for researchers and investors because it is a chaotic, non-linear, dynamic, non-stationary, noisy and quite difficult for these reasons the SM prediction price is one of an interesting field at present. SM movement affects by several factors, involve political situation, economic situation, disaster, trader's expectations, news and other sudden events where these factors may cause fluctuation in stock directions (Naeini *et al.*, 2010). Data mining techniques are dealing well with these difficulties, so, they have applied for this financial prediction (Ou and Wang, 2009).

Technical analysis can provide a trading signal (buy or sell) to investors by using a closing price an opening price, a high price, a low price and a volume of every day for stock exchange. Technical analysis is also generated TIs with a view to know directions of stock price and the momentum of buy and sell a stock or share (Naeini *et al.*, 2010). TIs are suitable methods to explore and prediction price of markets also which one of the well-established applications currently in practice to perform high returns (Ibrahim and Raahemifar, 2016). Typically, TIs are used in shorted-term predicting by investors mostly prefer. According to Atsalakis and Valavanis (2009), the SM predicting use TIs techniques as input in almost 20%.

The NASDAQ stock market is one of the most famous electronic stock exchanges in the United States for buying or selling stocks and shares with about 3,200 companies listed on it such as Microsoft, Google, Intel, Amazon and Oracle. Where it considered the standard index for US technology stocks. The National Association of Securities Dealers (NASD) to license investor's trade stocks on a computerized, speedy and transparent system created NASDAQ and it began trading on 8 Feb. 1971. The daily US NASDAQ prices show nonlinear, volatile, chaotic and dynamic (Banik and Khan, 2015).

The main objective from this study is to investigate historical data set on NASDAQ stock market using optimize multilayer perceptron neural network classification to help investors to know when to buy new stocks or to sell their stocks. Also, show the extent of the influence of TIs to improve the accuracy decision making to buying or selling in NASDAQ market.

Literature review: Many techniques of computational intelligence depends on numerical information about the market state and stocks are utilized for markets predicting. Some researchers employed artificial neural networks in their studies. Mingyue *et al.* (2016) are optimized the ANN Model using Genetic Algorithms (GA) and two types of input variables using TIs are applied to predict the direction of prices of the Japanese SM index. After that the authors compared between type 1 and 2 as input

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to model. Experimental results show that the type 2 provide prediction accuracy of the direction is 86.39% better performance of prediction accuracy from type 1 and therefore it is possible to improve the result of prediction model. Boonpeng and Jeatrakul (2016) classify three action of stock movement present a comparative study between the one with all and one with one neural network and traditional neural network. The fundamental analysis and the technical analysis are used for decision-making. Historical data collected from the Stock Exchange of Thailand for 7 years of the period from (03/01/2007) to (29/08/2014). They found that OAANN achieve better than OAONN and traditional NN Models. Chen and Jiang (2016) in introduce a comparative study between multiple stock price forecasting algorithms to forecast stock market. They compare PCA method and Genetic Algorithm (GA) to optimize the BP neural network. The experiments implemented on the Shanghai index data to make simulation. The results show the GABP better performance of forecasting accuracy. A comparative study between Back Propagation Neural Network (BPNN) and the Support Vector Machine (SVM) is introduced by Chen and He (2015) to pattern recognition. These methods are used to predict the SM. In addition, the authors apply Piecewise Linear Representation (PLR). The PLR is used for checking of watershed in their studies because it is good for mining worthy information from a time series. The investigation show that prediction in SVM obtains an average accuracy of 72.4% in compared with BBNN.

MATERIALS AND METHODS

Technical Indicators (TIs): Tis could be defined as the mathematical calculations results that long or short use of term investors in their charts (on other time frames sets) for confirming movement of the price that enables them predict stocks price evolution and thus form the signals of sell/buy trading positions are opened (Atsalakis and Valavanis, 2009). From one TI to another, intricacy differs but their performance does not necessarily depend on their complexity. Simple mathematical relationships can express some TIs that make them comprehend easily while others require various input parameters because they are expressed by relationships that are more complex.

TIs are classified as leading and lagging TIs. TIs Laggings are laid out to follow the action of the price. They are trend-following signal after trends starting. Simple Moving Average (SMA) is one of the moving averages types which gives few of the many examples of lagging TIs (Fernandez-Blanco *et al*., 2008). On the other hand, leading TIs generate signals which precede security price movement, i.e., the signal is generated before the reversal or new trend takes place. They retrospectively exhibit price momentum shape over a specific time interval. A leading TIs popular example is Relative Strength Index (RSI) (Fernandez-Blanco *et al*., 2008). In this study, fourteen TIs are used and these TIs are defined:

Simple Moving Average (SMA) (Zubayer *et al*., 2011): SMA can be measured by calculating the average price over an identified period's time. This process is repetitive on a daily basis to form own a time series of its own. The resulting formula is:

$$SMA = \frac{P_c(t)+P_c(t-1)+, ..., +P_c(t-n-1)}{n} \quad (1)$$

Where:
P_c = The close price of a given day
n = The period's time

Exponential Moving Average (EMA) (Zubayer *et al*., 2011): EMA can be measured by taking a weighted average of past prices. Gradually when prices becomes a past they will be weighted less. This means SM effect more recent EMA values result more than past values. EMA may be calculated by:

$$EMA = K(P_c-EMA(t-1))+EMA(t-1) \quad (2)$$

Where:

$$K = \frac{2}{(1+n)}$$

Weighted Moving Average (WMA) (Zubayer *et al*., 2011): WMA can be calculated by multiply factors of different weights to different data points. In WMA the oldest day takes weight equal to 1, the second oldest takes weight equal to 2, etc., up to newest day takes weight equal n:

$$WMA = \frac{nP_c+(n-1)P_{c-1}+,...,+2P_{c-n+2}+Pc-n+1}{n+(n-1)+,...,+2+1} \quad (3)$$

Moving Average Convergence Divergence (MACD) (Zubayer *et al*., 2011): MACD is collection of three signals which are measured by using EMA. Firstly, MACD that is the difference between 26 and 12 days EMA. Secondly, the signal that is the 9 days EMA of the MACD. Finally, histogram which is the difference between the signal and the MACD. When the MACD has different values for the MA, it is referred to as price oscillator. Price oscillator is used to detect variations of direction, momentum and strength in markets:

$$\text{MACD} = \text{EMA}(12)\text{-EMA}(26) \quad (4)$$

$$\text{Signal} = \text{EMA}(\text{MACD}, 9) \quad (5)$$

$$\text{Histogram} = \text{MACD-Signal} \quad (6)$$

Relative Strength Index (RSI) (Zubayer *et al*., 2011): It is an indicator of momentum that has a value between 0 and 100. RSI measures the direction and velocity of the movements of prices. Equation 7-9 is used for calculating RSI:

$$\text{RSI} = 100\frac{100}{-1+\text{RS}} \quad (7)$$

where RS is calculated by the following:

$$\text{RS} = \frac{\text{EMA}(\text{U}, \text{n})}{\text{EMA}(\text{D}, \text{n})} \quad (8)$$

When trading periods are in upward change use:

$$\text{U} = \text{P}_c(t)\text{-P}_c(t\text{-}1) \quad (9)$$

On the contrary when trading periods are in downward change use:

$$\text{D} = \text{P}_c(t\text{-}1)\text{-P}_c(t) \quad (10)$$

Bollinger Bands (BBs) (Atsalakis and Valavanis, 2009): BBs are involving volatility bands positioned above and below MA. It is believed that the interaction between these bands with the stock price give information about price movements in the future. BBs consist of a SMA: a lower BB and an upper BB:

$$\text{M} = \text{SMA}(\text{n})$$

$$\text{BB}_{\text{upper}} = \text{M}+\text{K}\sigma \quad (11)$$

$$\text{BB}_{\text{lower}} = \text{M}-\text{K}\sigma \quad (12)$$

Where:
σ = Standard deviation of P_c over n period's time
K = Specific multiple value. Commonly used K = 2 and n = 20

Stochastic (Atsalakis and Valavanis, 2009): It is a momentum indicator which points out the existing price over a period in relation to its price range. It consists of two lines the D and the K%. These lines demonstrate watershed predicted for a stock price. They are calculated:

$$\text{K\%} = 100\frac{\text{P}_c\text{-P}_L(\text{n})}{\text{P}_H(\text{n})\text{-P}_L(\text{n})} \quad (13)$$

Where:
P_c = Close price
P_L = Low price
P_H = High price over the past n period's time

Momentum (MOM) and Rate Of Change (ROC) (Zubayer *et al*., 2011): ROC is computed by taking the difference between current closing price from n days closing prices ago. After that it scale the result by the older closing prices. If scaling does not exist, indicator is called Momentum:

$$\text{Momentum} = \text{P}_c\text{-P}_c(\text{t-n}) \quad (15)$$

$$\text{ROC} = \frac{\text{P}_c\text{-P}_c(\text{t-n})}{\text{P}_c(\text{t-n})} \quad (16)$$

Commodity Channel Index (CCI) (Shynkevich *et al*., 2014): It calculates variation of market from its statistical means that are employed for identifying the cyclical orientation. It can be found by taking the difference between the current price and SMA of that price, after that the result is scaled by mean absolute deviation of this price:

$$\text{CCI} = \frac{\text{P}_t\text{-SME}(\text{P}_t)}{(0.015)\sigma_{\text{mad}}(\text{P}_t)} \quad (17)$$

σ_{mad} is the mean absolute deviation of P_t :

Williams R% (Zubayer *et al*., 2011): Current price relationship with high and low price for the past n days period time is shown by using Williams R%. R% is computed by:

$$\text{R\%} = \frac{\text{P}_H(\text{n})\text{-P}_c}{\text{P}_H(\text{n})\text{-P}_L(\text{n})} \quad (18)$$

where $P_H(n)$, $P_L(n)$: the high and low price, respectively over n period time.

AROON (Atsalakis and Valavanis, 2009): It Determines whether a stock is trending or not and how strong the trend. It is calculated depending on high and low price for last 14 days in this study. AROON is computed by:

$$\text{AROON}_{\text{up}} = ((14 - \text{High}(14\text{day}))/14)*100 \quad (19)$$

Table 1: Confusion matrix

	Predicted class	
Matrix	+	–
Actual class		
+	F_{00}	F_{01}
–	F_{10}	F_{11}

Table 2: Parameters briefing

Parameter	Formula
Precision	$\frac{F_{00}}{F_{00}+F_{10}}$
Recall	$\frac{F_{00}}{F_{00}+F_{01}}$
F1 measure	$\frac{2*F_{00}}{2*F_{00}+F_{01}+F_{10}}$
Specificity	$\frac{F_{11}}{F_{01}+F_{11}}$
Accuracy	$\frac{F_{11}+F_{00}}{F_{11}+F_{00}+F_{01}+F_{10}}$
MAE	$1/(n) \sum_{\downarrow}(k=0)^{\uparrow} n = (\| A_{\downarrow} (k\text{-}) P_{\downarrow} k$
RMSE	$\sqrt{\frac{1}{n}\sum_{k=0}^{n}(P_k\text{-}A_k)^2}$

$$AROON_{down} = \left((14 - \text{low}(14\text{ day})/14\right)*100 \quad (20)$$

True Range (TR) (Shynkevich *et al.*, 2014): It Shows degree of price volatility in market depending on high, low and close price:

$$TR = \max\left(|\text{high-low}|, |\text{high-}C_{t\text{-}1}|, |\text{low-}C_{t\text{-}1}|\right) \quad (21)$$

Performance metrics: In this study, several methods are used to evaluate the prediction models. Confusion Matrix (CM) is one of the most important of these methods. Additionally, two statistical measures are used; Root Mean Squared Error (RMSE) provide a complete picture of the error distribution and Mean Absolut Error (MAE) suitable to describe uniformly distributed errors.

CM is a conception of the performance of a supervised learning method. A CM is showed in Table 1, where F00 (true positive) is the number of records from class zero predicted correctly as class zero. F11 (true negative) is the number of records from class one predicted correctly as class one. F10 (false positive) is the number of records from class one predicted incorrectly as class zero. F01 (false negative) is the number of records from class zero predicted incorrectly as class one. Table 2 shows the formula of these methods.

Proposed system: Figure 1 shows the proposed system stages for enhancing the prediction of NASDAQ stock market.

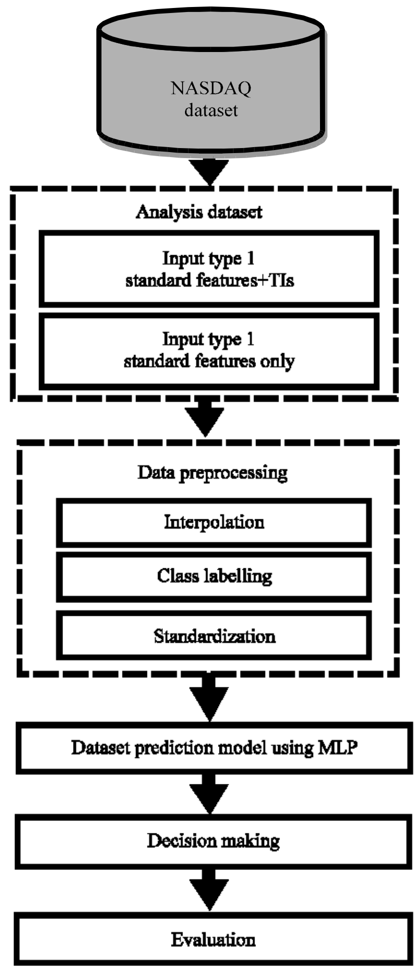

Fig. 1: The proposed system

Dataset: The samples of this study are taken from NASDAQ stock markets for experimental test with historical data set. The period of NASDAQ is selected from 10/09/2013-06/09/2016. The historical data are collected in daily basis (open, high, low, close, volume, adj close). In total 754 No. of instances from NASDAQ.

Generate technical indicators: Generating new input type 1 by using a set of Tis are widely recognized (Atsalakis and Valavanis, 2009). The historical data sets along with 14 TIs are used to effectively classify stocks actions. Accordingly, after this step the total number of features is 21.

Data preprocessing: There are three steps are employed for preprocessing stage or to prepare data into prediction model:

Interpolation: Linear regression is necessary used to address lost price records by replacing missing value with the existing adjacent prices.

Class labelling: The class attribute of future movements of closing prices are calculated using following equation. current data point of close price minus previous data point of close price, if positive and a traditional percentage gain at least 1% is denoted by a 'buy', otherwise is denoted by a 'sell'.

Standardization: The target of this step making the mean for each feature is equal to zero and a standard deviation is equal to one. All features is standardize by using this equation:

$$X_{ij} = \frac{X_{ij}\text{-}M_j}{SD_j} \tag{22}$$

Where:

X_{ij} = Data point in row i and column j
M_j = The mean of column j
Sd_j = Standard deviation of column j
X_{ij} = New data point in row i and column j

Prediction model using OMLP: The proposed model is based on developed prediction model through Optimize Multilayer Perceptron (OMLP) neural network trained using BP algorithm with one hidden layer by minimizing the given loss function (squared error). MLP is composed of three layers. Input is the first layer and it is compatible with input variables of a problem with a node for each input variable. The second layer is a hidden layer used to capture nonlinear relationships between variables. The third layer is an output layer used to provide the expected values. The output layer in this study have two neurons corresponding the prediction result. The connection between the input x_t and the output y_t is given by:

$$Y_i = w_0+\sum_{a=1}^{n} W_a . F\left[w_{0,a}+\sum_{b=1}^{m} W_{b,a} . x_t \right] \tag{23}$$

where $w_{b,a}$ (a = 0, 1, 2, ..., m; b = 1, 2, ..., n) and w_b (b = 0, 1, 2, ..., n) are the weights of network, m: input nodes, n: hidden nodes and F: a non-linear activation function. An approximate version of the logistic activation function is used in the hidden layer (Zurada and Jacek 1992.). It is given by:

$$\begin{gathered} y = 1.0+(-x)/4096.0;\ x = y*y; \\ x=\prod_{t=1}^{11} x\, F(x) = \frac{1}{1+e^{-x}} \end{gathered} \tag{24}$$

Sigmoid activation function is used in output layer (Luo *et al*., 2016). It is given by:

$$F(x)=\frac{1}{1+e^{-x}} \tag{25}$$

Two neurons are determined in hidden layer furthermore bias and the value of tolerance is equal to (1.0E-6). The BP algorithm is used to train MLP and the weights are optimized by reducing the error value. Definitely, the error reduction contribute in improving the prediction accuracy. Optimization model consists of many steps to improve the MLP algorithm:

MLP algorithm; Definition symbols:

X: vector of all weight in NNs
CF: Converges factor
Initialization

1. Initial weights to vector X
   Compute gradient to vector G using X
   Compute Hessian (second derivative) matrix H using X
   Ridge = 0.01,
2. For i=0 to max-iterations do
3. Compute the Jacobian gradient:
   $G_i = G_i$ +Ridge * X_i
4. While CF ? 0 Do
5. Find for the search direction d_i, $H_i d_i = -G_i$.
   Alternatively this step can be expressed as $d_i = -H_i^{-1} G_i$.
6. Take a step to get new variable values x_{i+1}. Normally, this is done as one Newton step d_i, however when the variable values are far from the function minimum, one Newton step may not guarantee a decrease of the objective function even if d_i is a descent direction. Thus , we are looking for a multiplier α such that α = argmin (f (x_i + d_i)) where f (.) is the objective function to be minimized. The search for á is carried out using a line search and once it is done, $x_{k+1} = x_i + d_i$
7. Calculate new gradient vector G_{i+1} and the new Hessian matrix H_{i+1} using x_{i+1}. Until CF = 0 then stop else go to step 2

RESULTS AND DISCUSSION

The suggested model is tested with cross-validation (10-fold) and holdout (70%) and model is compared with two inputs type (type 1 contains standard features plus TIs and type 2 contains standard features only) for checking the difference from the prediction on same points of view. The four confusion matrices are showed in Table 3-6. The outcomes of model with input type 1 are summarized in Table 7 and the similar parameters for model with input type 2 are summarized in Table 8.

Several measures are used to test the efficiency of the model include: the precision criterion shows that what percentage of increasing behaviors is accurately forecasted based on FP parameter. However, the criterion of precision only shows the increasing behaviors and so, it cannot identify the increasing behaviors. Therefore, the Recall Criterion is used for evaluating the numbers of true positive forecasts based on FN parameter (Altman and Bland, 1994).

Table 3: CM to cross validation type 1

	Predicted class	
Cross with TIs	Sell	Buy
Actual class		
Sell	263	76
Buy	75	340

Table 4: CM to cross validation type 2

	Predicted class	
Cross without TIs	Sell	Buy
Actual class		
Sell	35	304
Buy	33	382

Table 5: CM to holdout type 1

	Predicted class	
Holdout with TIs	Sell	Buy
Actual class		
sell	75	28
buy	28	95

Table 6: CM to Holdout type 2

	Predicted class	
Holdout without TIs	Sell	Buy
Actual class		
sell	22	81
buy	39	84

Table 7: Predictive efficiencies for NASDAQ with input type 1

Performance metrics	Cross-validation 10 (%)	Hold-out 70 (%)
Precision	80	75.200
Recall	80	75.200
F-measure	80	75.200
Specificity	81.7	74.200
Accuracy	79.9735	75.2212
MAE	0.2783	0.29100
RMSE	0.3839	0.40120

Table 8: Predictive efficiencies for NASDAQ using input type 2

Performance metrics	Cross-validation 10 (%)	Hold-out 70 (%)
Precision	53.800	44.1000
Recall	55.300	46.9000
F-measure	45.900	44.0000
Specificity	55.600	50.9000
Accuracy	55.305	46.9027
MAE	0.4959	0.50370
RMSE	0.4998	0.51100

Since, none of the above criteria is successful in estimating the quality of algorithm, so, accuracy is employed. Accuracy criterion estimates thequality of model. If the model can fairly identify the decreasing behaviors but fails toidentify the increasing behaviors and vice versa, the criteria of precision and recall becomes zero and vice versa. However, this problem is solved by the accuracy parameter. According to Table 7 and 8, the accuracy and all others measures performance of the suggested model using TIs are better than that model with standard features only.

CONCLUSION

TIs are demonstrated impact on the efficiency of the prediction model. This study displays a suggestion to develop the multilayer perceptron Neural Network classifier on the NASDAQ stocks data to generate decision actions that give references to purchase or sell stocks and shares in the SM. The investors can use a proposed model as useful tools to make the right decision on the market based on the analysis of the historical prices data of stocks to find any predictive information from these data. The accuracy and all others performance measures of the suggested model using TIs are better than that model without using TIs. Finally, this study is found the Accuracy rate is raised to 79.97% instead of 55.3% for standard features only.

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