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An Optimized Feed Forward Neural Network for Reducing Error Based Stock Market Prediction

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Abstract: Stock market prediction is an interest financial topic that has attracted the attention of researchers for the last years. Data mining has been effectively used in financial predicting, hence, researchers have explored technical indicators to optimize the parameters. The main objective of this study is to improve prediction for stock market using a developed method of feed forward neural networks based on optimization model which aims to reduce the error factor depending on the Jacobian vector and Lagrange multiplier according to the converges factor reach to zero. Also, a benchmark of Iraq (Bank of Baghdad) is built and comparted with DOWJONES and S and P500 stock markets. After evaluation stage. The results are compared by K-nearest-neighbors method and decision tree algorithm. The proposed method satisfies better results of prediction according to the accuracy and root mean secured error performance measures.

Key words: Stock market prediction, developed feed forward neural network, optimization, technical indicators, lagrange multiplier, accuracy

INTRODUCTION

Stock Market (SM) analysis is a wide area for researchers and inventors because of the stock market prediction price is one of an interesting problem in financial time series. The SM is an effective part of any country's economy. It plays a significant role in the industry that in the end effect on country's economy growth. The SM is a public place where companies are allowed to trading of moneys through the sale or purchase of shares and stocks after determining the price agreed upon in advance (Chavan and Patil, 2013).

Because of the connection among inputs and outputs are variable, nonlinear and volatile in nature the estimation of stock market future values has become hard task. Also choosing a suitable training and prediction method is still very critical problem (Navale *et al*., 2016).

SM prediction is the process to determine the future value of company stock based on its historical data. Predicting the stocks prices can be done in two way first: fundamental analysis at most be determined by mathematical data of a company (Edwards *et al*., 2001). Second: technical analysis at most be determined by technical indicators and machine learning, the analyst using numerical factors include daily ups and downs, volume of stock, tendency pointers, highest and lowest prices of a day, directories, simple moving average and others. Analysts have attempted to discover some accurate arithmetic model which can allocate these input to predict the desirable output (Yefimochkin, 2011). Technical Indicators (TIs) are a sequence of new data points that are resolved from applying mathematical equations on the price values of a SM. TIs are one of the first parameters used to predict the price of shares and stocks. These are categorized into two groups, lagging and leading indicators. The lagging indicators follow the price action, for example Simple Moving Average (SMA). Leading indicators are determined to drive price activity. Also, they create the signal before the new movement or problem happens, for examples Relative Strength Index (RSI) as the most common type of leading Tls (Ferna-Blancondez *et al*., 2008).

Literature review: This study, a review of current techniques are accomplished for stock market classification using machine learning and technical analysis. Where an overview is showed of the study that helped as monitors to this work.

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

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show that prediction in SVM obtains an average accuracy of 72.4% in compared with BBNN. 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 seven years of the period from (03/01/2007) to (29/08/2014). They found that OAANN achieve better than OAONN and traditional NN models.

By Zaamout and Zhang (2012) implemented new ensemble method to increase performance of the neural network classification. The first method combines the output of a set of neural networks together. Additionally, the second method improved the accuracy by feeding the output of NNs and repeat this process until the error does reduce sufficiently. Better accuracy is achieved at the cost of computing time.

Finally, in 2015 a comparative study between discrete features as input to C4.5 decision tree and numerical feature as input to C4.5 introduced by Panigrahi and Mantri (2015) to forecasting stock market. Where the historical data and twelve technical indicators are calculated over numerical dataset of NSE nifty and BSE sensex as input to classification model. The authors was found that a text based decision tree model is better accuracy than usual decision tree.

MATERIALS AND METHODS

Stock market prediction techniques: Decision Tree (DT) (Han *et al*., 2011) is commonly classification technique which it depends on creation a structure as tree. Its result are very interpretable because they generated rules which are easy to understand but the outcome have to be represented in categorical data. Hence, DT are less efficient for prediction when the features are numerical (Panigrahi and Mantri, 2015).

There are many machine learning method in data mining where lazy learning algorithm is the simplest one because it does not need for any model in training. The model is built in classification or prediction is required (Han *et al*., 2011). Therefore, KNN is one of lazy learning type which predicts classes of entity based on the K nearest training instances in the feature space. The classification of KNN entity can be done by collect the majority votes for its neighbors. How to determine the correct value of K in this method is considered a problem.

An Artificial Neural Network (ANN) (Han *et al*., 2011) is a computational model that is an interconnected group of nodes or neurons intended to represent the network in the brains. They are widely used in SM prediction because of their ability to learn complex patterns. It is strong with respect to noisy, uncertainty and missing data and it is able to learn and adapt to the environment. NN is appropriate to the problem that algorithm is inexpressible or complete search is impracticable (Mingyue *et al*., 2016). In this study, the NN named feed forward is used in this study.

Performance metrics: In this study, two methods are used to evaluation the prediction models; Accuracy (ACC) and Root Mean Squared Error (RMSE). ACC is the number of accurate predictions divide on the entire number of completed predictions by model Micheline *et al*. (2012):

$$\text{ACC} = \frac{f11+f00}{f11+f00+f01+f10} \tag{1}$$

- True positive (f 11): is the no. of records from class 1 correctly predict as class 1
- True negative (f 00): is the no. of records from class 0 correctly predict as class 0
- False positive (f 01): is the nos. of records from class 0 incorrectly predict as class 1
- False negative (f 10): is the nos. of records from class 1 incorrectly predict as class 0

RMSE is a regularly used measure of the differences between actual values and predicted values by a model Micheline *et al*. (2012):

$$\text{RMSR} = \sqrt{\frac{1}{n}\sum_{k=0}^{n}\left(p_k - A_k\right)^2} \tag{2}$$

Where:

P = Predicted value of k

A = Actual value of k

Methods of testing

Hold-out method (H_0): The original data in this method is divided into two disjoint sets, called the training and the test sets, respectively. Since the training set union and intersection of testing set is the empty set. The split differs from a fifty-fifty to two-three for training and one-three for testing (Tan *et al*., 2005).

Cross-Validation (CV): The original data in this method partitioning into K equal subsets where each records or subset are used the K-1 of times for training and exactly once for testing. The total error is calculated by aggregate the errors founded through all k runs divided on k as the average across runs (Tan *et al*., 2005).

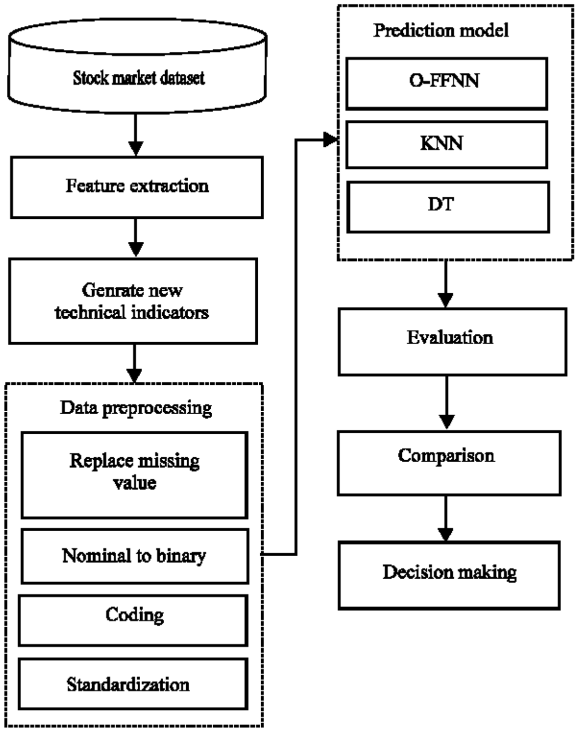

Fig. 1: The proposed system

Proposed system: Figure 1 show the architecture of the proposed system for SM prediction for understanding is easy and quickly. The detailed description of the proposed system is as follows:

Stock market dataset

Benchmark of Iraq: During our study of global stock markets, including the Iraq Stock Exchange and their impact on the economy of the country. We noticed that there was not organize dataset for stock market in Iraq but we founded just daily and weekly-scattered reports, despite the fact that trading in the stock market of Iraq began in 2004 and it includes more than 100 companies. For this reason, a regular benchmark for one of large shareholding companies is created, a Bank of Baghdad as a case study, if successful can be applied to the rest of the companies. Seven traditional features is discovered for this market of the last three years, after that technical indicators have been implemented on this data to improve accuracy of prediction the future prices.

Dataset: The study based on experimental test with historical data set from three main stock markets like (S and P500, DOW and Iraq). The period of S and P500 and DOW are selected from 18/10/2013 to 14/10/2016 while the period of Iraq is selected from 20/8/2013 to 1/9/2016.

Table 1: Summarization of dataset

Data set	DOW	S and P500	Iraq
Period time	3 years	3 years	3 years
No. of features	7	7	7
No. of Indicators	20	20	20
No. of Instances	754	754	660
No. of classes	3 (Buy, Sell, Hold)	2 (Buy, Sell)	3 (Buy, Sell, Hold)

The historical data are collected in daily basis (open, high low, close, volume, adj close). In total 754 nos of instances from (DOW, S and P500) while 660 instances of Iraq dataset. Table 1 is displayed summarization of dataset will be using.

Feature extraction: Extract traditional feature from stock market dataset like:

- Date: the trade day of the work
- Open: stock's opening price for a specific day
- Low: the lowest closing price of the stock during the day
- High: the highest closing price of the stock during the day
- Close: a stock's closing price on any given day
- Volume: volume of Stock transactions (buy/sell)
- Adj. close: an adjusted closing price is a stock's closing price for a specific trading day. The adjusted closing price is regularly used when investigative historical yields or performing an exhaustive analysis on historical returns

Generate new technical indicators: In this study, technical indicators are used as inputs to the model of prediction to improve the accuracy. The historical data set along with 20 technical indicators have been displayed in Table 2 to be an effective illustration of stock price can use to effectively classify stocks actions. Since, after this step has become the number of features is 27. In addition one investor's decision making i.e., 'class'.

Pre-processing stage: At this stage, the data is processed and prepared into prediction step, the lost values are addressed by replacing missing value with average value in column that contains lost values as well as the nominal features is converted into binary features, after that the class attribute is calculated using two different equations. First, current data point of close price minus previous data point of close price, if positive is denoted by a 'buy', negative is denoted by a 'sell' otherwise is denoted by a 'hold'. Next, a traditional percentage gain is required before classifying a point as 'buy'. Where if at least 1% gain is wanted with once a day from the previous day's close then will be classified as 'buy', otherwise it is classified 'sell'.

Table 2: Description of technical indicators

Technical Indicators	Name	Description
SMA	Simple Moving Average	Simple moving average of the close price for last 30 days
WMA	Weighted Moving Average	Weighted moving average of the close price for past 30 days
EMA	Exponential Moving Average	Exponential moving average of the close price for last 30 days
AROON	Aroon	Determines whether a stock is trending or not and how strong the trend is. It is calculate depending on High and Low price for last 14 days
ROC	Rate of Change	Compute rate of change relative to previous trading intervals, we use 10 days intervals
RSI	Relative Strength Index	Suggests the overbought and oversold market signal. Relative Strength Index is related to 14 days max. avg. and min. avg
CCI	Commodity Channel Index	Identifies cyclical turns in stock price. It is calculate depending on High, Low and Close price for last 14 days
MACD	Moving Average Convergence Divergence	Moving average convergence divergence is the difference between 9 days EMA and 26 days EMA
MINMAX	Minimum and maximum price	Lowest and highest close values for the last 30 days
VAR	Variance	Variance of the close price for last 5 days with deviation of 1
BBANDS	Bollinger bands	It is plotted two standard deviations away from a simple moving average
MOM	Momentum	The difference between previous close and current close for last 10 days
STOCH	Stochastic	The stochastic oscillator is a momentum indicator comparing the closing price of a stock market to the range of its prices over 5 days
R (%)	Williams %R	Determines where today's closing price fell within the range on last 10 day's transaction
TRUE_RANGE	Average true range	Shows volatility of market depending on high, low and close price
AVG	Average price	A representative measure of a range of prices that is depending on open, low, high and close price
MEDIAN	Median price	Determines Median price of market depending on high and low price
WCP	Weighted Close Price	The weighted close formula calculates the average value of daily prices but gives more weight to the close price
STDDEV	Standard Deviation	A measure of the dispersion of the close price for last 5 days from its mean
TSF	Time Series Forecasting	Calculates the linear regression of 14 days price

$$C_i = \Delta \text{Close price} \tag{3}$$

$$C_i = \begin{cases} X & \text{if } close_i > close_{i-1} \\ O & \text{if } close_i = close_{i-1} \\ -1 & \text{if } close_i < close_{i-1} \end{cases} \tag{4}$$

$$X = \begin{cases} 1 & \text{if } gain_i \geq 1 \\ -1 & \text{if otherwize} \end{cases} \tag{5}$$

$$Gain_i = \frac{close_i - close_{i-1}}{close_i} * 100 \tag{6}$$

where, i from1 to total historical data. Finally, all features is standardize by using this equation:

$$X_{ij} = \frac{X_{ij} - M_j}{SD_j} \tag{7}$$

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 has a mean of 0 and a standard deviation of 1

Prediction model: In this study, two popular classifiers are used for comparison with the proposed model, first:the C4.5 decision tree algorithm is applied to classify future SM price which extended to the (id3) algorithm. Where this algorithm deal with numerical features and it uses gain ratio measure to determine the best split. Second: k-nearest-neighbors method is also applied to classify future SM price. In our study, after trying and error k equal to 15 as the best value was founded to achieve higher accuracy of method.

The proposed model is based on developed new predict model through Optimize Feed Forward Neural Network (O-FFNN) with one hidden layer by minimizing the given loss function (squared error). two neurons is determined in hidden layer furthermore, bias the penalization on the weights size is determined equal to (0.01) and the value of tolerance equal to (1.0 E-6). In addition an approximate sigmoid function version of the logistic function is used as the activation function for the hidden layer to improve speed. In the output layer, the sigmoid function is used for classification the direction of stocks. Finally, accuracy and RMSE are employed to evaluation the proposed model and compared it with C4.5 and KNN.

Optimization model consist of many steps to improve the FFNN algorithm for reducing the error value. Definitely, the error reduction contribute in improving the prediction accuracy.

Algorithm; Definition symbols:

X: vector of all weight in NNs
SPDM: Symmetric Positive Definite Matrix
LT: Lower Triangle
DM: Diagonal Matrix
CF: Converges Factor
α: Step length

1. Initialization
   Initial weights to vector X
   Compute gradient to vector G using X
   Compute matrix factorization of SPDM using LT and DM
   Ridg = 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. Apply the langrage multiplier to test the convergence.
6. Compute newton direction to vector D using inverse G
7. Find the upper bound of X to determine the best value according to
   $X_{i+1} = X_i + \alpha D_i$
8. Update G depend on X, LT, DMA and LM until CF = 0 STOP
9. Go to step 2

RESULTS AND DISCUSSION

The OFFNN, DT and KNN testing with Cross-Validation (CV) 10-fold and Hold-Out (HO) 70% and compared for checking the difference from the prediction on same points of view. The outcomes of accuracy to these methods are summarized in Table 3 and the similar parameters for root mean squared error are summarized in Table 4.

To interpret the percentage of accuracy (the percentage of correctly classified instances) with which the model can forecast the proposed O-FFNN model performs better over its counterpart. From Table 3, it can be shown that the average percentage of accuracy is 92.68% for the proposed model which vis much higher than the other models. Similarly, from Table 4, it can be shown root mean squared error is lower in proposed model which indicates the better efficiency of the model. Also The outcomes of accuracy to DOWJONES, S and P500 and Iraq are visualized in Fig. 2-4, respectively.

Table 3: Comparative accuracy for three stock markets

Accuracy	DOW (%)	S and P500 (%)	Iraq (%)
O-FFNN			
CV 10	95.89	92.31	89.85
HO 70	95.13	92.92	87.88
K-NN			
CV 10	69.36	57.03	49.70
HO 70	69.91	56.64	50.51
DT			
CV 10	71.22	73.21	58.79
HO 70	74.78	68.58	57.07

Table 4: Comparative RMSE for three stock markets

RMSE	DOW	S and P500	Iraq
O-FFNN			
CV10	0.1505	0.2352	0.2395
HO 70	0.1551	0.2177	0.2543
K-NN			
CV 10	0.5332	0.6546	0.5791
HO 70	0.4993	0.6573	0.5744
DT			
CV 10	0.3857	0.6546	0.4884
HO 70	0.3640	0.6573	0.4704

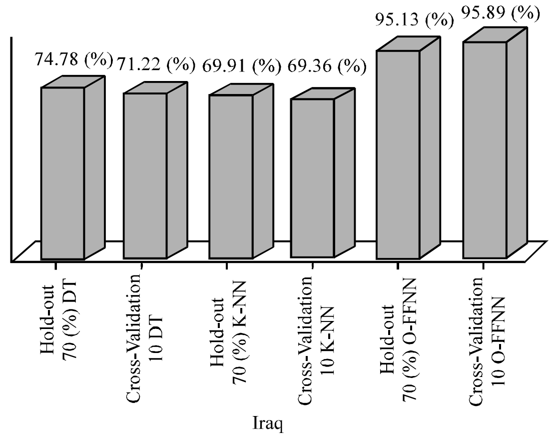

Fig. 2: Accuracy of DOWJONSE

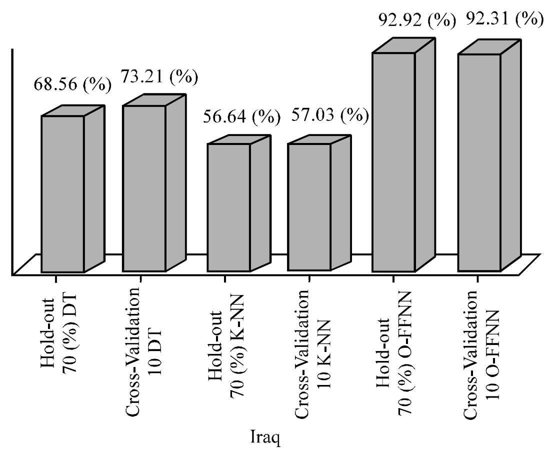

Fig. 3: Accuracy of S and P500

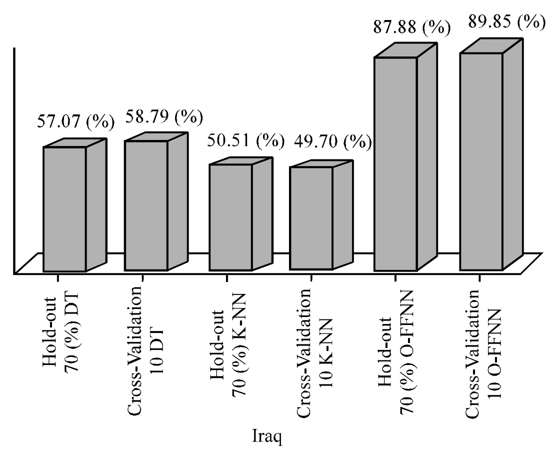

Fig. 4: Accuracy of Iraq

CONCLUSION

This study displays a suggestion to develop the feed forward neural network classifier on the historical stocks data to generate decision procedures that give references to purchase or sell stocks and shares in the stock market. In addition, a benchmark of Iraq is built where bank of baghdad is taken as a case study to prove construction precision. Then technical indicators are demonstrated impact on the efficiency of the prediction model. The investors can be 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 results for the proposed model are perfect after compared with another prediction models (KNN and DT). Also, benchmark of Iraq is proven accuracy when comparing with DOWJONES and S and P500 after implementation on these three models.

REFERENCES

Boonpeng, S. and P. Jeatrakul, 2016. Decision support system for investing in stock market by using OAA-neural network. Proceedings of the 8th International Conference on Advanced Computational Intelligence (ICACI), February 14-16, 2016, IEEE, Chiang Mai, Thailand, ISBN:978-1-4673-7780-5, pp: 1-6.

Chavan, P.S. and S.T. Patil, 2013. Parameters for stock market prediction. Intl. J. Comput. Technol. Appl., 4: 337-340.

Chen, X. and Z.J. He, 2015. Prediction of stock trading signal based on support vector machine. Proceedings of the 8th International Conference on Intelligent Computation Technology and Automation (ICICTA), June 14-15, 2015, IEEE, Nanchang, China, ISBN:978-1-4673-7644-0, pp: 651-654.

Edwards, R.D., W.H.C. Bassetti and J. Magee, 2001. Technical Analysis of Stock Trends. 8th Edn., CRC Press, Boca Raton, Florida, USA.,.

Fernandez-Blanco, P., D.J. Bodas-Sagi, F.J. Soltero and J.I. Hidalgo, 2008. Technical market indicators optimization using evolutionary algorithms. Proceedings of the 10th Annual Conference Companion on Genetic and Evolutionary Computation, July 12-16, 2008, ACM, Atlanta, Georgia, USA., ISBN:978-1-60558-131-6, pp: 1851-1858.

Han, J., M. Kamber and J. Pei, 2011. Data Mining: Concepts and Techniques. 3rd Edn., Morgan Kaufmann Publishers, USA., ISBN-13: 9780123814791, Pages: 744.

Micheline, K., J. Han and J. Pei, 2012. Data Mining: Concepts and Techniques. 3rd Edn., Elsevier, Amsterdam, Netherlands, ISBN:978-0-12-381479-1, Pages: 673.

Mingyue, Q., L. Cheng and S. Yu, 2016. Application of the artifical neural network in predicting the direction of stock market index. Proceedings of the 10th International Conference on Complex, Intelligent and Software Intensive Systems (CISIS), July 6-8, 2016, IEEE, Fukuoka, Japan, ISBN:978-1-5090-0988-6, pp: 219-223.

Navale, G.S., N. Dudhwala, K. Jadhav, P. Gabda and B. Kishor, 2016. Prediction of stock market using data mining and artificial intelligence. Intl. J. Comput. Appl., 134: 9-11.

Panigrahi, S.S. and J.K. Mantri, 2015. A text based decision tree model for stock market forecasting. Proceedings of the International Conference on Green Computing and Internet of Things (ICGCIoT), October 8-10, 2015, IEEE, Noida, India, ISBN:978-1-4673-7911-3, pp: 405-411.

Tan, P.N., M. Steinbach and V. Kumar, 2005. Introduction to Data Mining. 1st Edn., Pearson Addison Wesley, New York, ISBN-13: 978-0321321367, Pages: 769.

Yefimochkin, O., 2011. Fundamental: Using macroeconomic indicators and genetic algorithms in stock market forecasting. Master Thesis, Instituto Superior Tecnico, Lisbon, Portugal.

Zaamout, K. and J.Z. Zhang, 2012. Improving neural networks classification through chaining. Proceedings of the 22nd International Conference on Artificial Neural Networks, September 11-14, 2012, Springer, Lausanne, Switzerland, pp: 288-295.