



## A Back Propagation Based Deep Neural Network for Stock Market Prediction

*Shraddha Jain<sup>1</sup>, Megha Gupta<sup>2</sup>*

*M.Tech Scholar (CSE)<sup>1</sup>, Department of Computer Science and Engineering, PCST, Indore (India)*

*Assistant Professor (CSE)<sup>2</sup> Department of Computer Science and Engineering, PCST, Indore (India)*

### ABSTRACT

Stock Market prediction is a category of time series prediction which extremely challenging due to the dependence of stock prices on several financial, socio-economic and political parameters etc. Moreover, small inaccuracies in stock market price predictions may result in huge losses to firms which use stock market price prediction results for financial analysis and investments. Off late, artificial intelligence and machine learning based techniques are being used widely for stock market prediction due to relatively higher accuracy compared to conventional statistical techniques. The proposed work employs the steepest descent based scaled conjugate gradient (SCG) algorithm along with the data pre-processing using the discrete wavelet transform (DWT) for stock market prediction. It has been shown that the proposed system attains lesser mean square percentage error compared to previously existing technique [1].

Keywords: Stock Market Forecasting, Artificial Neural Network (ANN), Back Propagation, Scaled Conjugate Gradient (SCG), Discrete Wavelet Transform (DWT), Mean Absolute Percentage Error (MAPE).

### 1. INTRODUCTION

Stock Markets have long remained one of the one avenues on the forefront which is crucial for the operations of most of the top most companies. Several decisions pertaining to investments, shares etc. depend on the behavior of the stocks of a company. The stock price values are often leveraged by financial and investment firms for gaining profits and investing. However, the volatile nature of the stock markets make it a risky proposition. Therefore, estimating the future trends in stock prices is somewhat mandatory for firms analyzing stock prices and aiming to gain leverage. This calls for stock market forecasting or stock market prediction. Stock market prediction is basically a time series prediction problem. Mathematically:

$$P = f(t, v) \quad (1)$$

Here,

P represents stock price

f represents a function of

t is the time variable

v are other influencing global variables

The dependence of stock process over time makes it somewhat predictable under similar other conditions of global influencing variables. However, even the slightest of changes can derail the prediction completely.

Statistical techniques are not found to be as accurate as the contemporary artificial intelligence and machine learning based approaches [6]. In this paper, a back propagation based scaled conjugate gradient algorithm is used in conjunction with the discrete wavelet transform (DWT) for forecasting stock

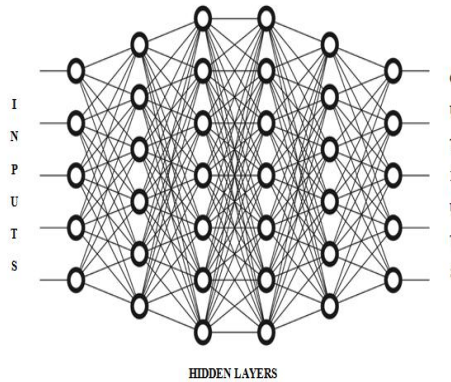
\* Corresponding author.

E-mail address: [jainshraddha1204@gmail.com](mailto:jainshraddha1204@gmail.com)

market trends. The evaluation of the proposed approach has been done based on the mean absolute percentage error (MAPE). A comparative MAPE analysis has also been done w.r.t. previously existing techniques.

**2 DEEP LEARNING**

Deep learning has evolved as one of the most effective machine learning techniques which has the capability to handle extremely large and complex datasets [8]. It is training neural networks which have multiple hidden layers as compared to the single hidden layer neural network architectures [9]-[10]. The architectural view of a deep neural network is shown in figure 1. In this case, the outputs of each individual hidden layer is fed as the input to the subsequent hidden layer. The weight adaptation however can follow the training rule decided for the neural architecture. There are various configurations of hidden layers which can be the feed forward, recurrent or back propagation etc.



**Fig.1 The Deep Neural Network Architecture**

The figure above depicts the deep neural network architecture with multiple hidden layers. The output of the neural network however follows the following ANN rule:

$$Y = \sum_{i=1}^n X_i \cdot W_i + \theta_i \quad (2)$$

Where,

X are the inputs

Y is the output

W are the weights

Θ is the bias.

Training of ANN is of major importance before it can be used to predict the outcome of the data inputs.

**3. BACK PROPAGATION**

Back propagation is one of the most effective ways to implement the deep neural networks with the following conditions:

- 1) Time series behavior of the data
- 2) Multi-variate data sets
- 3) Highly uncorrelated nature of input vectors

The essence of the back propagation based approach is the fact that the errors of each iteration is fed as the input to the next iteration. [11]–[13]. The error feedback mechanism generally is well suited to time series problems in which the dependent variable is primarily a function of time along with associated variables. Mathematically,

$$Y = f(t, V_1 \dots V_n) \quad (3)$$

Here,

Y is the dependent variable

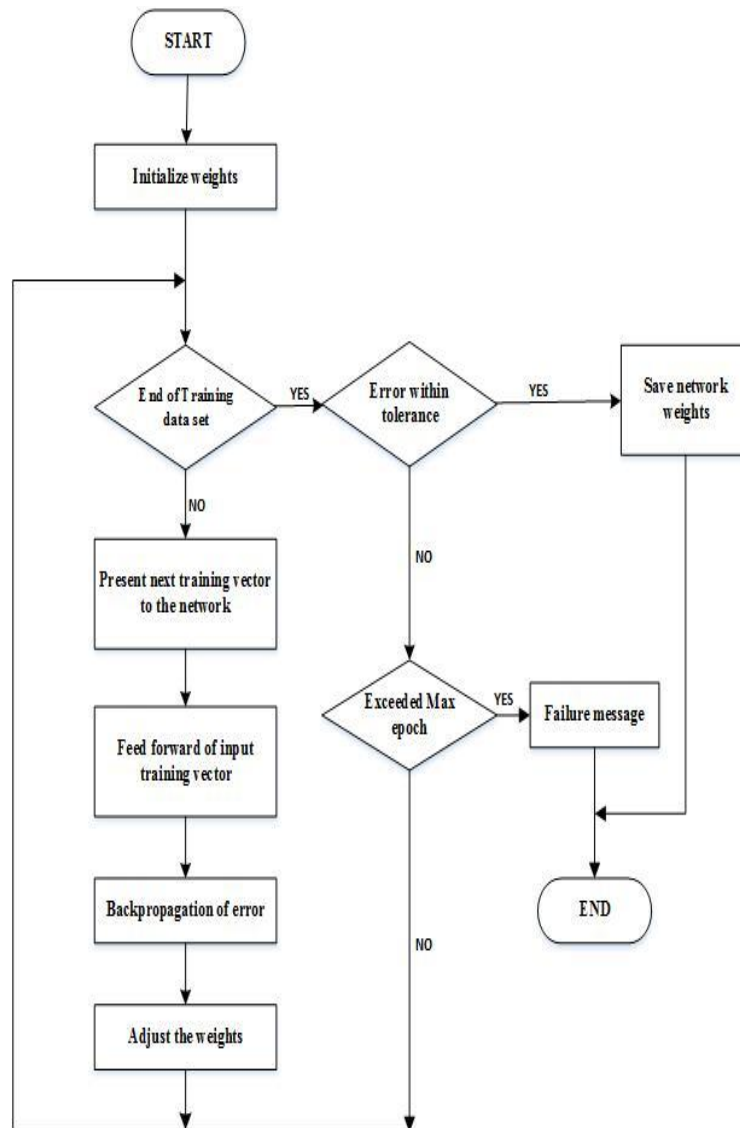
f stands for a function of

t is the time metric

V are the associated variables

n is the number of variables

The back propagation based approach can be illustrated graphically in figure 2.



**Fig.2 Concept of Back Propagation**

In case of back propagation, the weights of a subsequent iteration doesn't only depend on the conditions of that iteration but also on the weights and errors of the previous iteration mathematically given by:

$$W_{k+1} = f(W_k, e_k, V) \quad (4)$$

$W_{k+1}$  are the weights of a subsequent iteration

$W_k$  are the weights of the present iteration

$e_k$  is the present iteration error

$V$  is the set of associated variables

In general, back propagation is able to minimize errors faster than feed forward networks, however at the cost of computational complexity at times.

However, the trade off between the computational complexity and the performance can be clearly justified for large, complex and uncorrelated datasets for cloud data sets [14]-[15].

#### 4 GRADIENT DESCENT BASED TRAINING

The gradient descent algorithms (GDAs) generally exhibit:

- 1) Relatively lesser memory requirement

2) Relatively faster convergence rate

The essence of this approach is the updating of the gradient vector  $g$ , in such a way that it reduces the errors with respect to weights in the fastest manner. Mathematically, let the gradient be represented by  $g$  and the descent search vector by  $p$ , then

$$p_0 = -g_0(5)$$

Where,

$g_0$  denotes the gradient given by  $\frac{\partial e}{\partial w}$

The sub-script 0 represents the starting iteration

The negative sign indicates a reduction in the errors w.r.t. weights

The tradeoff between the speed and accuracy is clearly given by the following relations:

$$W_{k+1} = W_k - \alpha g_x, \quad \alpha = \frac{1}{\mu} \quad (6)$$

Here,

$w_{k+1}$  is the weight of the next iteration

$w_k$  is the weight of the present iteration

$g_x$  is the gradient vector

$\mu$  is the step size for weight adjustment in each iteration.

There are several ways to implement the back propagation technique in the neural networks. One consideration however always remains that of the least time and space complexity so as to reduce the amount of computational cost that is associated with the training algorithm. The essence of the scaled conjugate gradient algorithm is the fact that it has very low space and time complexity making it ideally suited to large data sets to be analyzed in real time applications where the time is a constraint. The training rule for the algorithm is given by:

$$A_0 = -g_0 \quad (7)$$

$A$  is the initial search vector for steepest gradient search

$g$  is the actual gradient

$$w_{k+1} = w_k + \mu_k g_k \quad (8)$$

Here,

$w_{k+1}$  is the weight of the next iteration

$w_k$  is the weight of the present iteration

$\mu_k$  is the combination co-efficient

## 5. THE DISCRETE WAVELET TRANSFORM

The wavelet transform is an effective tool for removal of local disturbances. Stock prices show extremely random behavior and local disturbances. Hence conventional Fourier methods do not render good results for highly fluctuating data sets. Mathematically, the wavelet transform can be given as:

$$Z(S, P) = \int_{-\infty}^{\infty} z(t) ((S, P, t)) dt \quad (9)$$

Here,

$S$  denotes the scaling operation

$P$  denotes the shifting operation

$t$  denotes the time variable

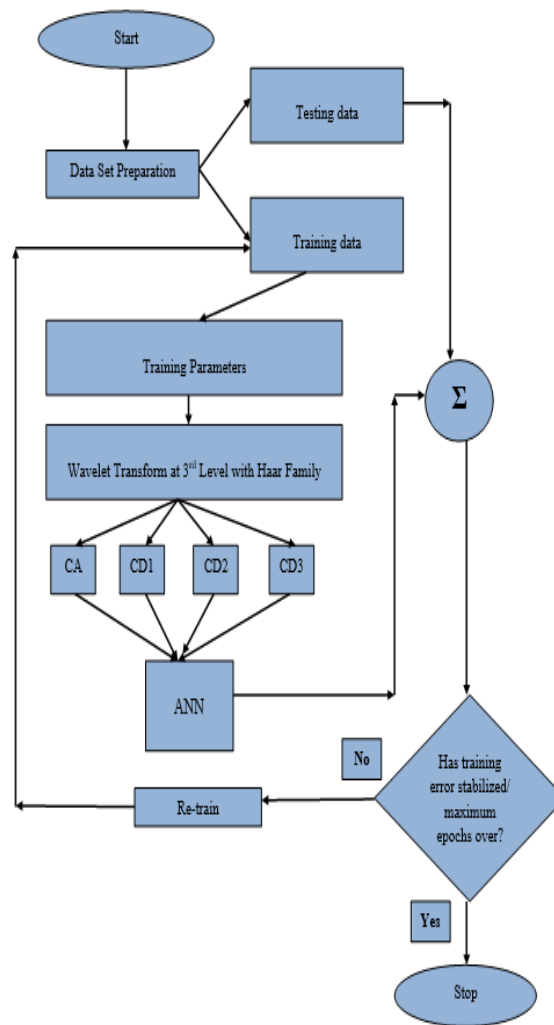
$Z$  is the image in transform domain

$z$  is the image in the spatial domain

The major advantage of the wavelet transform is the fact that it is capable of handling fluctuating natured data and also local disturbances. The DWT can be defined as:

$$W\Phi(J_0, k) = \frac{1}{\sqrt{M}} \sum_n S(n) \cdot \Phi(n)_{j_0'k} \quad (10)$$

The entire methodology can be understood using the system flowchart depicted below.



**Fig.3 Flowchart of Proposed System**

The data is divided in the ration of 70:30 for training and testing data set bifurcation.

The final performance metrics computed for system evaluation are:

1) Mean Absolute Percentage Error (MAPE)

$$MAPE = \frac{100}{M} \sum_{t=1}^N \frac{E - E_t}{E_t} \quad (11)$$

Here  $E_t$  and  $E_t^-$  stand for the predicted and actual values respectively.

The number of predicted samples is indicated by M.

2) Regression

The extent of similarity between two variables is given by the regression where the maximum value is 1 and the minimum is 0.

## 6. RESULTS

The results have been evaluated based on the following parameters:

1. (MAPE)
2. Regression
3. MSE w.r.t. the number of epochs

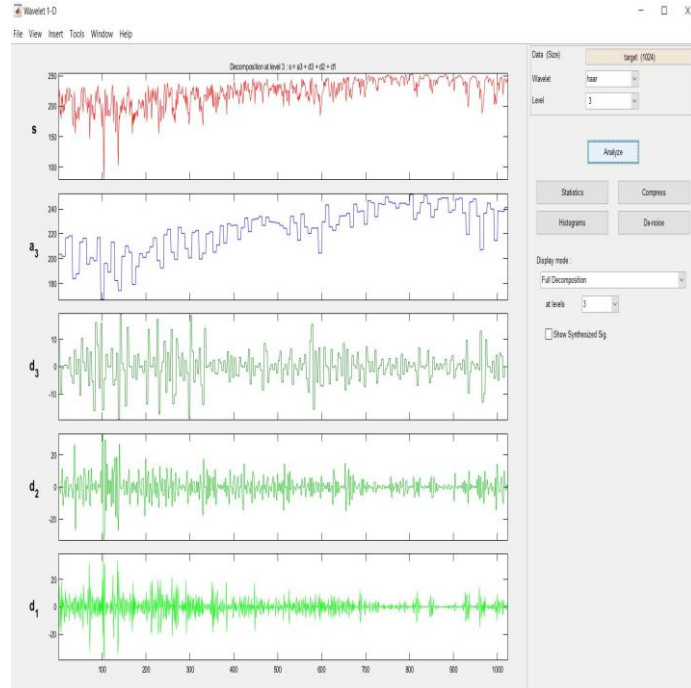


Fig.4 Decomposition of Data at level 3 using Haar Wavelets

The figure above depicts the Haar wavelet decomposition of the stock data at level 3.

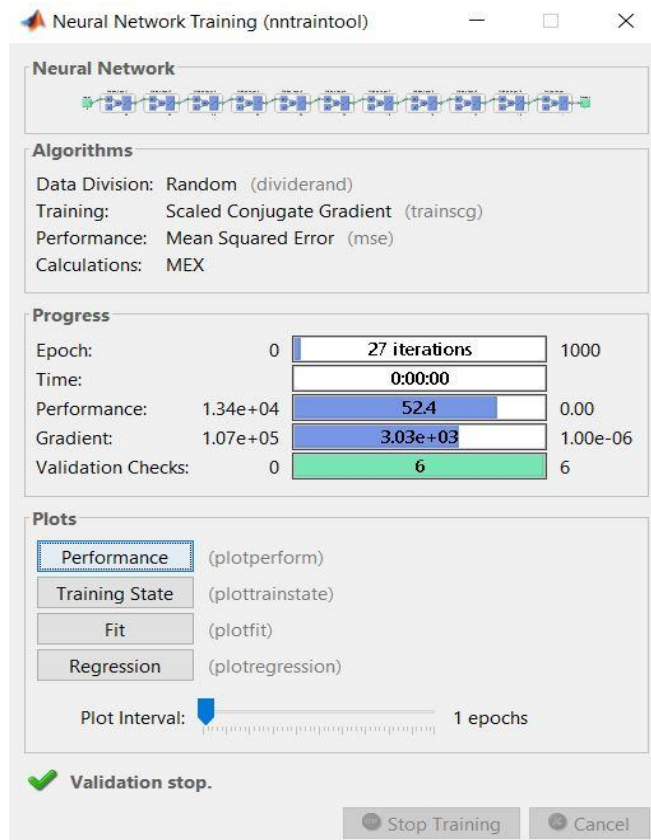
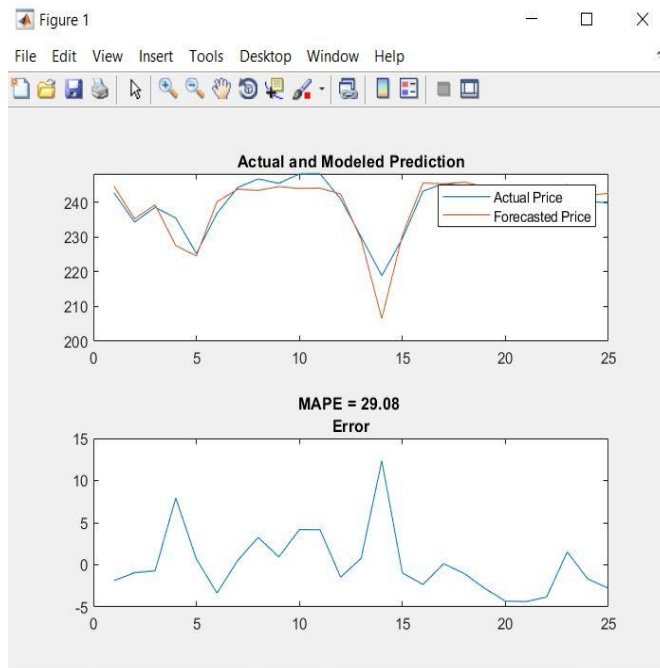


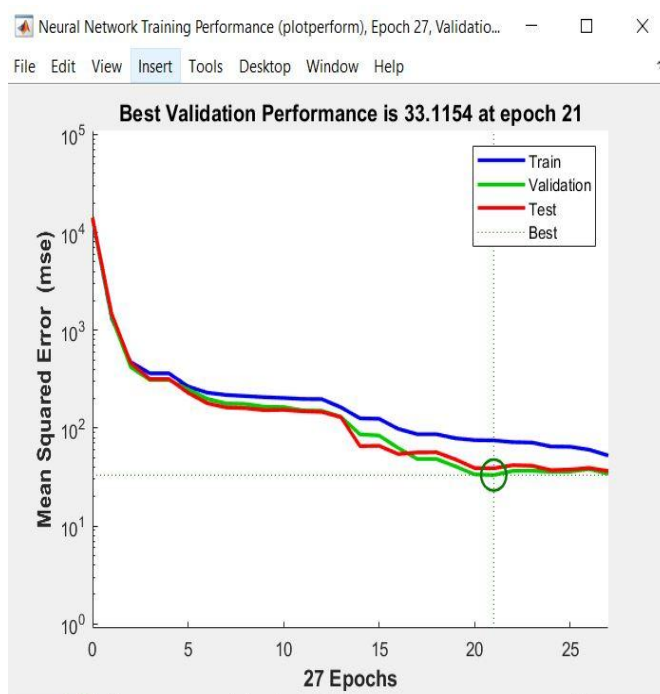
Fig.5 Designed Neural Network

The figure above depicts the training parameters of the deep neural network based on the SCG learning algorithm.



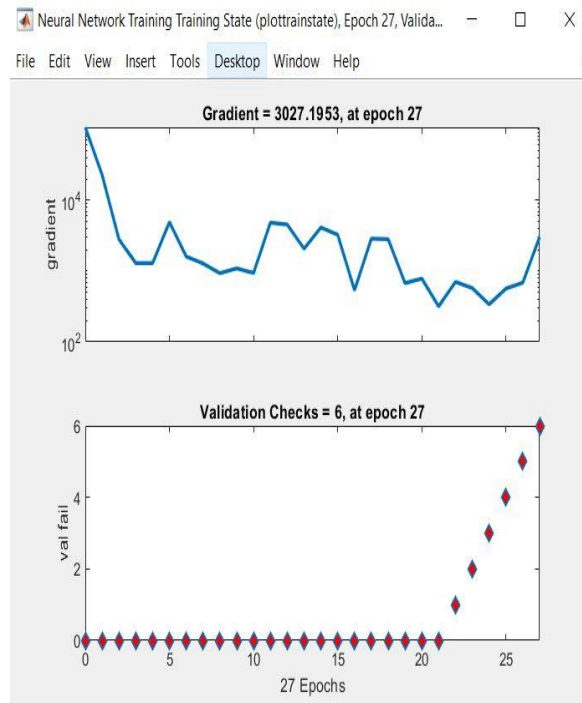
**Fig.6 Predicted and Actual Stock Behavior**

The figure above depicts the predicted and actual stock behavior.



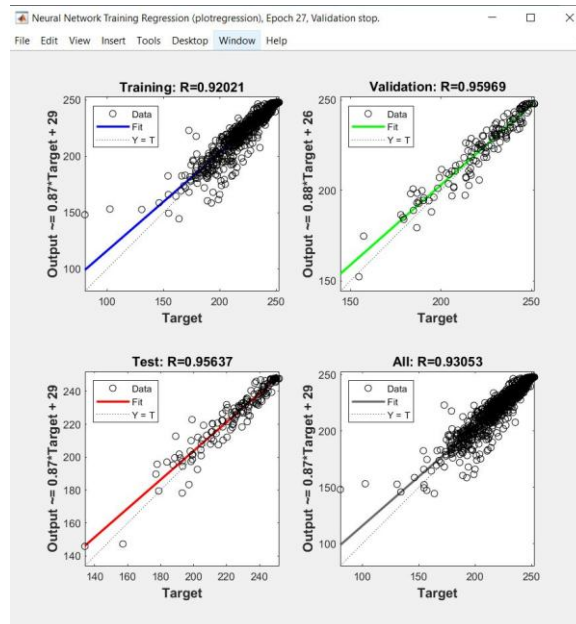
**Fig.7 Variation of MSE with respect to epochs**

The figure above depicts the variation of the mse w.r.t. the epochs



**Fig.8 Training Parameters**

The figure above depicts the training states as a function of iterations.



**Fig.9 Regression Analysis**

From the above figures, it can be concluded that the proposed system attains the following results:

- 1) MAPE of Proposed work=29.08%
- 2) Accuracy of Proposed work=70.92
- 3) Accuracy of Previous work [1]=57%
- 4) Regression of Proposed work= 0.93 (overall)
- 3) Number of iterations is 27

A comparative accuracy analysis w.r.t. previous work is given by:



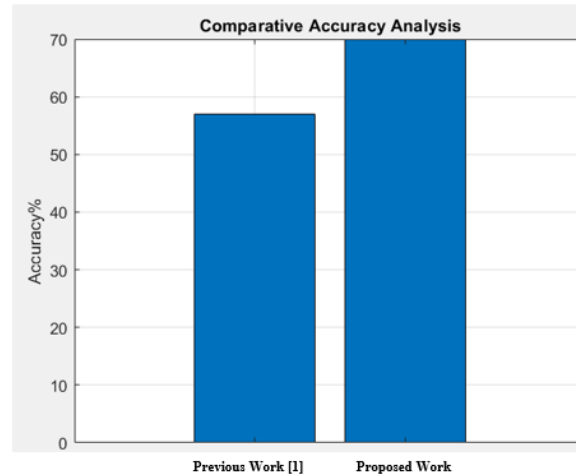


Fig.10 Comparative Accuracy Analysis w.r.t. Previous Work [1]

## 7. CONCLUSION

It can be concluded from previous discussions that stock market prediction is a category of time series prediction with high sensitivity and dependence on external factors. Hence it is often challenging to attain high levels of accuracy in prediction. In the proposed approach a back propagation based deep learning model is proposed with a 1-10-1 configuration. The adaptive gradient descent algorithm (GDA) is used to train the neural network. Data pre-processing is done using the discrete wavelet transform. It has been shown that the proposed work attains a mean absolute percentage error of 29.08% compared to a mean absolute percentage error of 57% of previous work [1]. Moreover, the regression is 0.93 at the number of epochs being 27. Thus the proposed system is able to achieve low errors, higher accuracy and relatively low number of iterations. Also the proposed work outperforms previously existing systems in terms of the accuracy for the benchmark datasets used.

## REFERENCES

- [1] Xiongwen Pang, Yanqiang Zhou, Pan Wang, Weiwei Lin, Victor Chang., "An innovative neural network approach for stock market prediction", Springer 2018.
- [2] John M. Kirimi, Christopher A. Moturi, "Application of Data Mining Classification in Employee Performance Prediction", International Journal of Computer Applications (0975 – 8887) Volume 146 – No.7, July 2016
- [3] Thomas Fischer, Christopher Krauss, "Deep Learning with long short term memory networks for financial market predictions", Elsevier 2017
- [4] Daša Dragnić, "Impact of Internal and External Factors on The Performance of Fast-Growing Small And Medium Business", Preliminary communication, Accepted: 26. 05. 2014 UDC: 005.71-022.51/.55(497.5)
- [5] Amin HedayatiMoghaddam, MoeinHedayatiMoghaddam, MortezaEsfandiyari, "Stock market index prediction using artificial neural network", Journal of Economics, Finance and Administrative Science 21 (2016) 89–93,
- [6] Aditya Bhardwaj, Yogendra Narayan, Vanraj, Pawan, Maitreyee Dutta, "Sentiment Analysis for Indian Stock Market Prediction Using Sensex and Nifty", Procedia Computer Science 70 (2015) 85 – 91
- [7] MehakUsmani, Syed Hasan Adil, Kamran Raza, Syed SaadAzhar Ali, "Stock Market Prediction using Machine Learning Techniques", DOI: 10.1109/ICCOINS.2016.7783235
- [8] Reza Hafezi, Jamal Shahrabi, EsmaeilHadavandi, "A bat-neural network multi-agent system (BNNMAS) for stock price prediction: Case study of DAX stock price", Applied Soft Computing 29 (2015) 196–210
- [9] Xiongwen Pang, Yanqiang Zhou, Pan Wang, Weiwei Lin, Victor Chang, "An innovative neural network approach for stock market prediction", Springer Science+Business Media, LLC, part of Springer Nature 2018
- [10] Lili Wang, Zitang Wang, Shuai Zhao, Shaohua Tan, "Stock market trend prediction using dynamical Bayesian factor graph", Expert Systems with Applications, No. of Pages 9, 24 March 2015
- [11] Adam Atkins, MahesanNiranjan, Enrico Gerding, "Financial news predicts stock market volatility better than close price", The Journal of Finance and Data Science 4 (2018) 120-137
- [12] AparnaNayak, M. M. ManoharaPai and Radhika M. Pai, "Prediction Models for Indian Stock Market", Procedia Computer Science 89 ( 2016 ) 441 – 449
- [13] Xingyu Zhou, Zhisong Pan, Guyu Hu, Siqi Tang, and Cheng Zhao, "Stock Market Prediction on High-Frequency Data Using Generative Adversarial Nets", Hindawi Mathematical Problems in Engineering Volume 2018, Article ID 4907423, 11 pages
- [14] Sahar Sohngir, Dingding Wang, Anna Pomeranets and Taghi M. Khoshgoftaar, "Big Data: Deep Learning for financial sentiment analysis", J Big Data (2018) 5:3
- [15] MrugaGurjar, ParthNaik, Gururaj Mujumdar, Prof. Tejaswita Vaidya, "Stock Market Prediction Using ANN", International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056, Volume: 05 Issue: 03 | Mar-2018
- [16] Raphael H. Heiberger, "Predicting economic growth with stock networks", Physica A 489 (2018) 102–111

- [17] YanhuiGuo, Siming Han, Chuanhe Shen, Ying Li, Xijie Yin, and Yu Bai, "An Adaptive SVR for High-Frequency Stock Price Forecasting", 2169-3536 2018 IEEE, VOLUME 6, 2018
- [18] Xi Zhang, Siyu Qu, Jieyun Huang, Binxing Fang, and Philip Yu, "Stock Market Prediction via Multi-Source Multiple Instance Learning", 2169-3536 2018 IEEE, VOLUME 6, 2018
- [19] Bruno Miranda Henrique, ViniciusAmorimSobreiro, Herbert Kimura, "Stock price prediction using support vector regression on daily and up to the minute prices", The Journal of Finance and Data Science 4 (2018) 183-201
- [20] Wen Fenghua, Xiao Jihong, He Zhifang, Gong Xu, "Stock Price Prediction Based on SSA and SVM", Procedia Computer Science 31 ( 2014 ) 625 – 631