# Predicting the Trends in Stock Movement Using Deep Neural Networks

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***Abstract*— Stock market forecasting is challenging and subject to uncertainties. Market dynamics can be influenced by a wide range of factors, including economic data, geopolitical events, investor sentiment, and unexpected events like natural disasters or health crises. Forecasting methods vary, ranging from technical analysis (studying historical price and volume data) to fundamental analysis (evaluating a company's financial health) to quantitative models and machine learning algorithms. Investors and analysts should approach stock market forecasts with caution, considering the limitations and potential biases of the methods used. Diversification, risk management, and a long-term perspective are often recommended to navigate the inherent uncertainty of financial markets. This paper presents a deep neural network model with data pre-processing for stock market forecasting. The results in terms of percentage error clearly indicate that the proposed approach performs better than existing work in the domain.**

***Keywords—Time Series Forecasting, Stock Trends, Neural Networks, Regularization, MAPE, Regression.***

## I. INTRODUCTION

Stock market movements are often considered leading indicators of the overall economy's health. Policymakers and central banks monitor stock markets to gain insights into economic trends and potential policy adjustments. [1]. Traders, both short-term and long-term, use stock market forecasts to develop trading strategies. These strategies may involve technical analysis, fundamental analysis, or a combination of both. [2]. Stock market movements are often considered leading indicators of the overall economy's health. Policymakers and central banks monitor stock markets to gain insights into economic trends and potential policy adjustments. It's important to note that while stock market forecasting has its uses, it is inherently challenging and subject to various uncertainties. Markets are influenced by a multitude of factors, including economic data, geopolitical events, investor sentiment, and unforeseen events (such as natural disasters or crises), making accurate predictions difficult. Many investors and analysts use a combination of tools and approaches, including fundamental analysis, technical analysis, machine learning models, and expert opinions, to make more informed decisions in the dynamic world of stock trading. Mathematically:

$$\boldsymbol{Stock\ Prices} = \boldsymbol{f}(\boldsymbol{time}, \boldsymbol{features}) \quad \textbf{(1)}$$

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 [3].

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 conjugation with the discrete wavelet transform (DWT) for forecasting stock 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 [4].

## II. DATA DRIVEN MODELS

Deep learning has evolved as one of the most effective machine learning techniques which has the capability to handle extremely large and complex datasets [5]. It is training neural networks which have multiple hidden layers as compared to the single hidden layer neural network architectures [6]-[7].

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 [8].

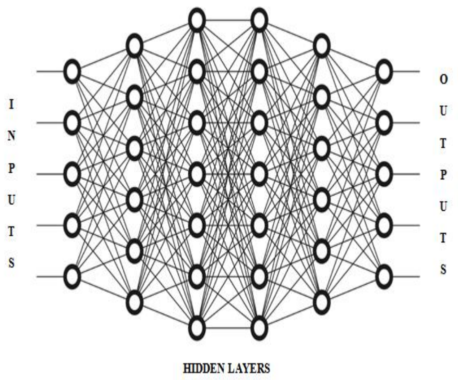


**Fig.1 The Deep Neural Network Architecture**

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:

$$Y = f\left(\sum_{i=1}^{n} X_i . W_i + \theta_i\right) \quad (2)$$

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.

## III. BACK PROPAGATION

Back propagation is one of the most effective ways to implement the deep neural networks with the following conditions [9]:

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. [10]-[11]. 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,

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

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.

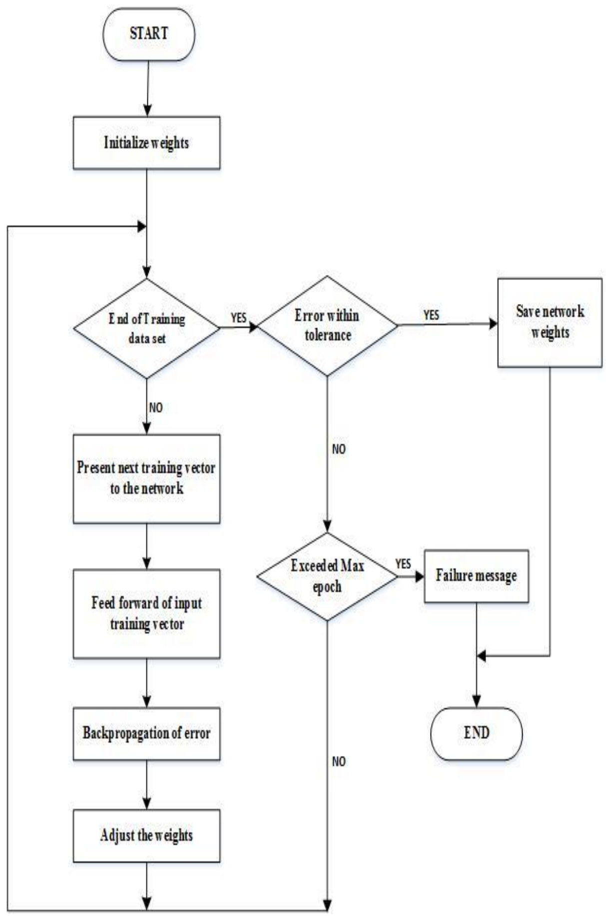


**Fig.2 Concept of Back Propagation**

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 [12]:

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

Here,
$W_{k+1}$ 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 [13].

## IV. 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 as 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 [14]:

$$\boldsymbol{p_0 = -g_0} \tag{5}$$

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 [15].

The tradeoff between the speed and accuracy is clearly given by the following relations [16]:

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

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

μ is the step size for weight adjustment in each iteration.

There are several ways to implement the back propagation technique in the neural networks [17]. 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 [18]:

$$\boldsymbol{A_0 = -g_0} \tag{7}$$

A is the initial search vector for steepest gradient search

g is the actual gradient

$$\boldsymbol{w_{k+1} = w_k + \mu_k g_k} \tag{8}$$

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

## V. 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 [19]

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

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 [20]:

$$\boldsymbol{W\Phi\,(Jo, k) = \frac{1}{\sqrt{M}} \sum_n S(n).\Phi(n)_{jo\prime k}} \tag{10}$$

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

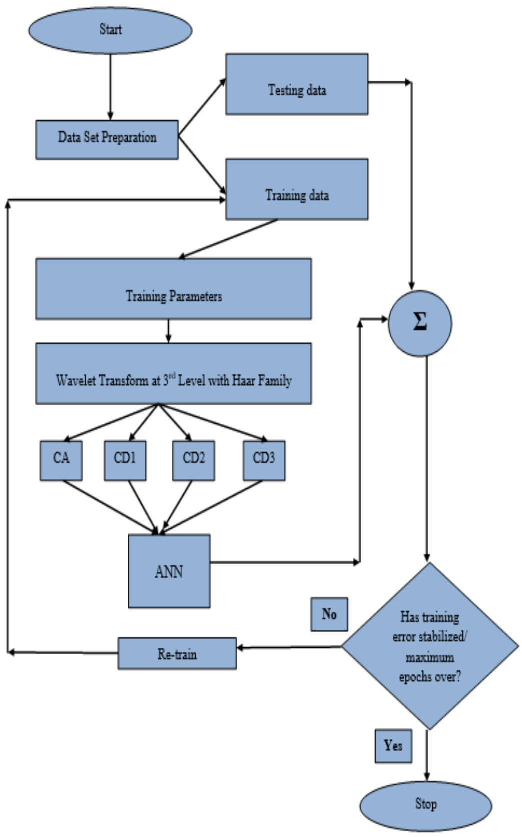


**Fig.3 Flowchart of Proposed System**

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)

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

Here $E_t$ and $E_t^{\sim}$ 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.

## VI. RESULTS

The results have been evaluated based on the following parameters:

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

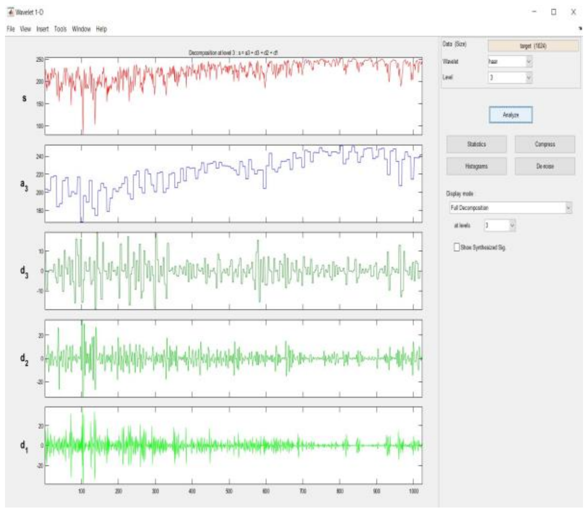

**Fig.4 Decomposition of Data at level 3 using Haar Wavelets**

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

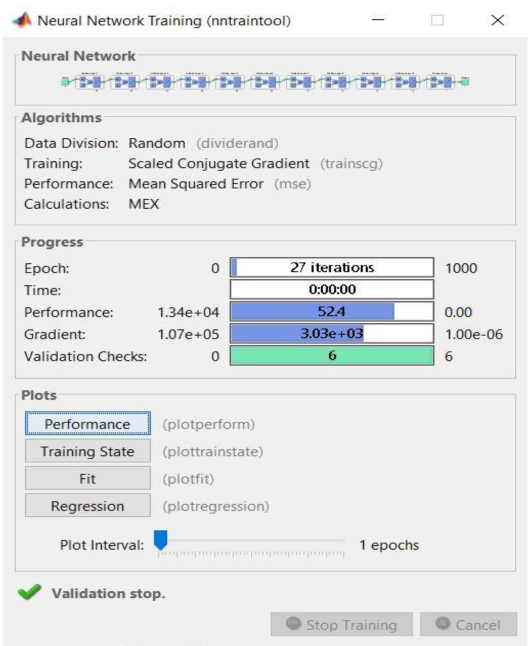


**Fig.5 Designed Neural Network**

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

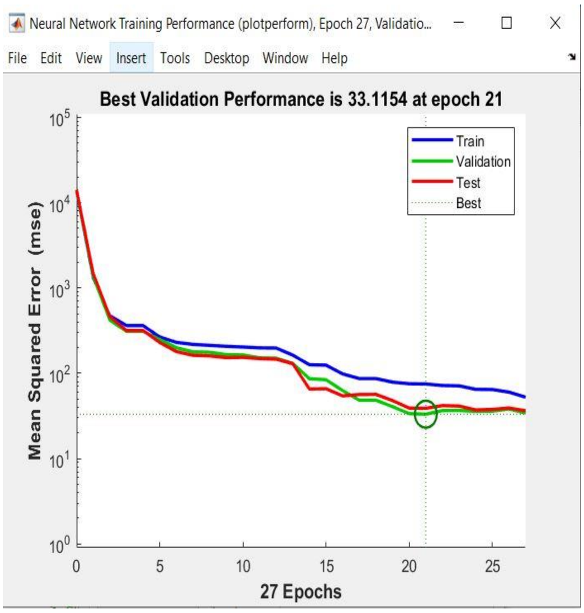


**Fig.6 Variation of MSE with respect to epochs**

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

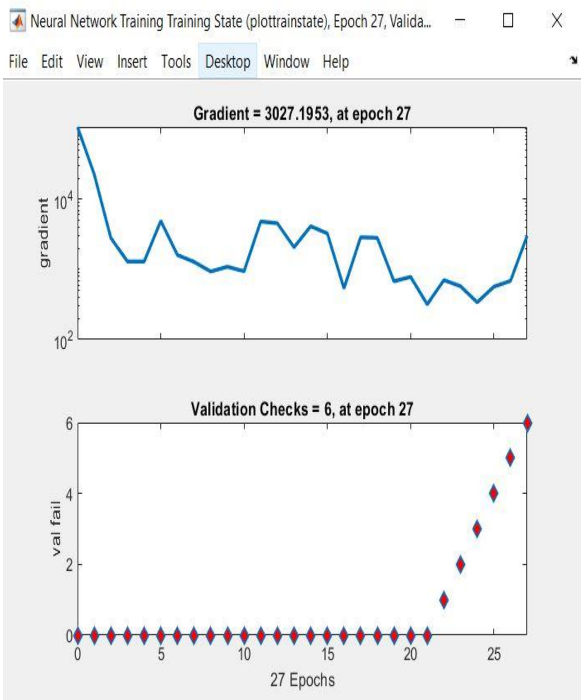


**Fig.7 Training Parameters**

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

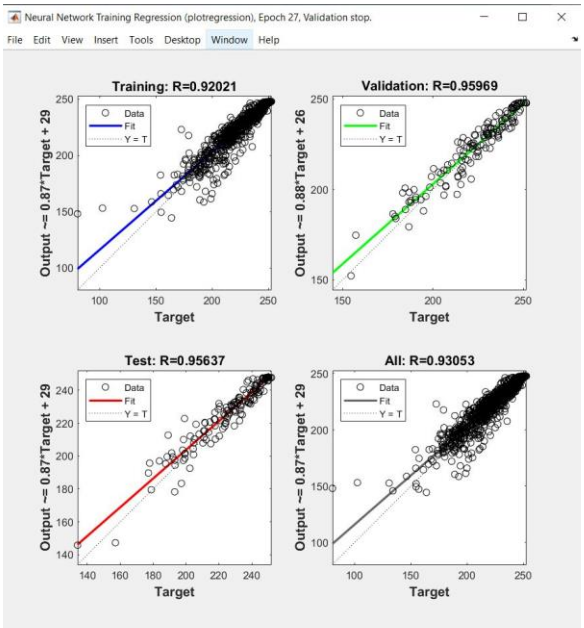


**Fig.8 Regression Analysis**

The training, testing, validation and overall regression values are depicted in figure above. The forecasting results for the different stocks are now presented. The Apple and Tesla stock forecasting results have been shown here. The MAPE indicates the percentage error.

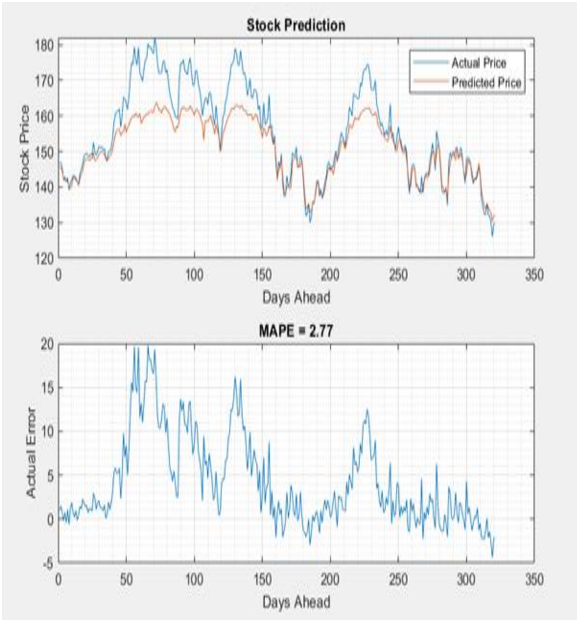


**Fig.9 Forecasting: Dataset: Apple**

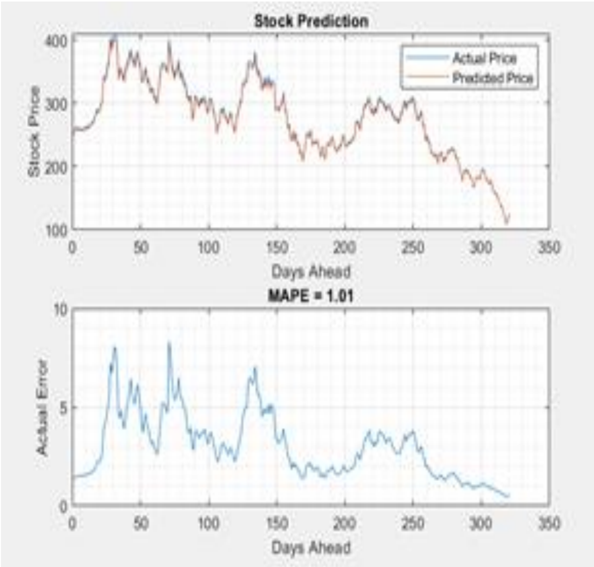


**Fig.10 Forecasting: Dataset: Tesla**

A comparison with existing work in the domain is presented next:

**Table 1. Summary of Results:**

| S.No. | Parameter | Value |
|---|---|---|
| 1. | Dataset | Tesla, Google |
| 2. | Splitting Ratio | 70:30 |
| 3. | Pre-Processing | Haarlet |
| 4. | ML Model | DNN |
| 5. | Regression Overall | 0.930 |
| 6. | %error (Tesla) | 1.0 |
| 7. | %error (Google) | 2.7 |
| 8. | %error [21] | 43 |
| 9. | %error [22] | 5.6 |
| 10. | %error [23] | 7.7 |

It can be observed that the proposed work attains lower percentage error and hence higher accuracy compared to existing work in the domain, which are cited in [21], [22]., [23] in table 1.

## CONCLUSION

**Stock market forecasting is a topic of significant interest and importance for various stakeholders, including investors, traders, financial analysts, and policymakers. Several reasons drive the need for stock market forecasting. Investors use stock market forecasts to make informed decisions about buying, holding, or selling stocks. Accurate forecasts can help investors optimize their portfolios and potentially earn higher returns. Forecasting helps investors and businesses assess and manage risks associated with stock market investments. Understanding potential market movements can aid in implementing risk mitigation strategies The proposed approach based on steepest descent attains a very low % error for multiple datasets and thus clearly proves high forecasting accuracy. Also, a comparative analysis with existing work shows that the proposed approach performs better compared to baseline approaches.**

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