# Forecasting The Movement of Stock Trends Employing Deep Neural Networks

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***Abstract-*** *Forecasting the stock market is difficult and unpredictable. Numerous factors, such as economic statistics, geopolitical developments, investor mood, and unforeseen events like natural catastrophes or health crises, can have an impact on market dynamics. There are many different ways to forecast a market: from quantitative models and machine learning algorithms to technical analysis, which examines past price and volume data, to fundamental analysis, which assesses a company's financial stability. Forecasts on the stock market should be viewed cautiously by analysts and investors due to the limits and potential biases of the methodology employed. It is often advised to use risk management, diversification, and a long-term outlook to deal with the inherent volatility 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:

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

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].

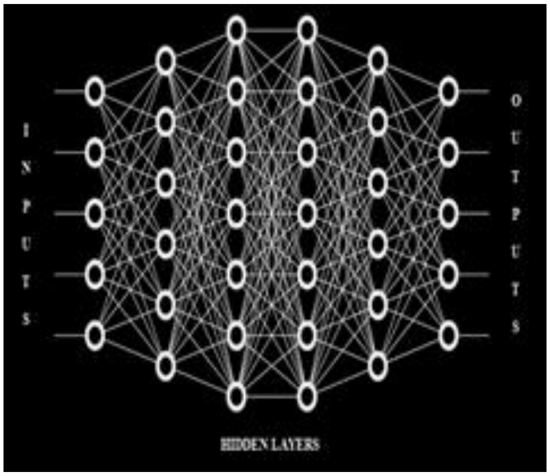


**Fig.1 The Deep Neural Network Architecture**

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:

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

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,

$$Y = f(t, V_1 \dots . V_n) \quad \textbf{(3)}$$

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.

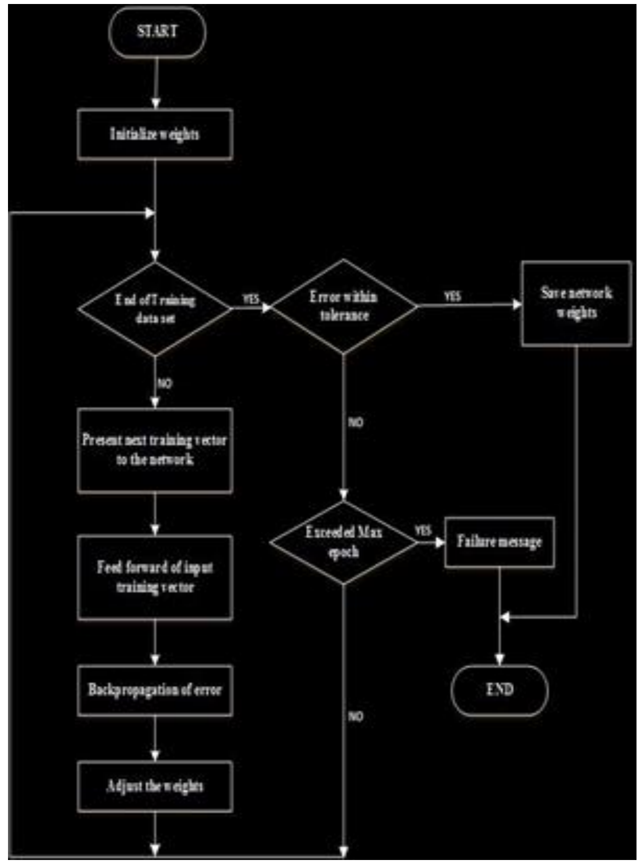


**Fig.2 Concept of Back Propagation**

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]:

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

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]:

$$p_0 = -g_0 \quad (5)$$

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]:

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

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
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]:

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

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

## 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]

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

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 [20]:

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

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 $E_t^{\sim}$ 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

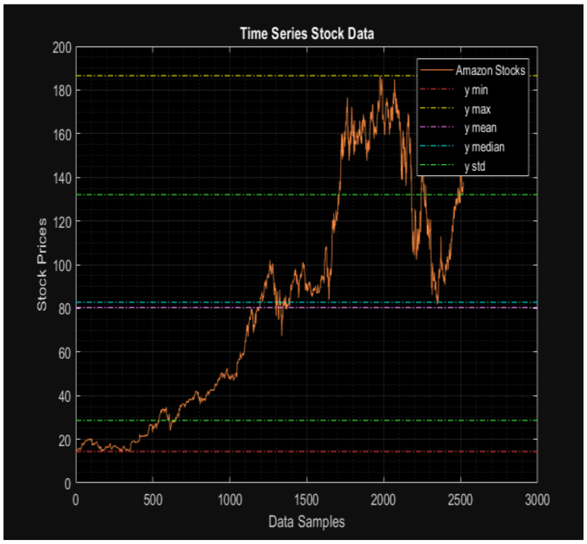


**Fig.3Raw Data Statistics**

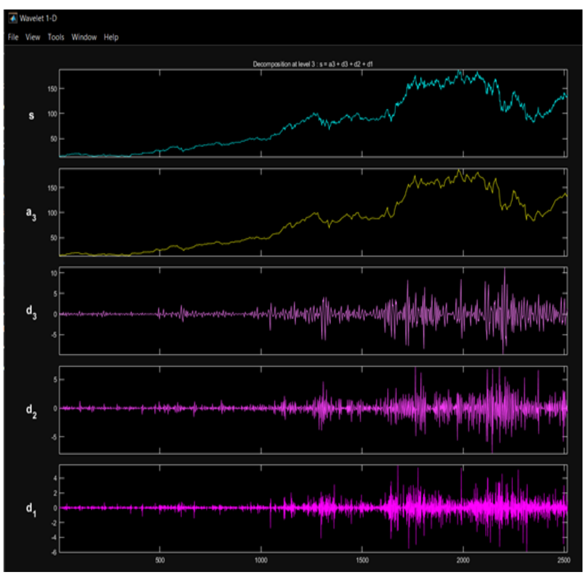


**Fig.4 Data Filtering**

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

The training, testing, validation and overall regression values are depicted in figure above. The forecasting results for the different stocks are now presented. The MAPE indicates the percentage error. The stocks chosen are depicted next:

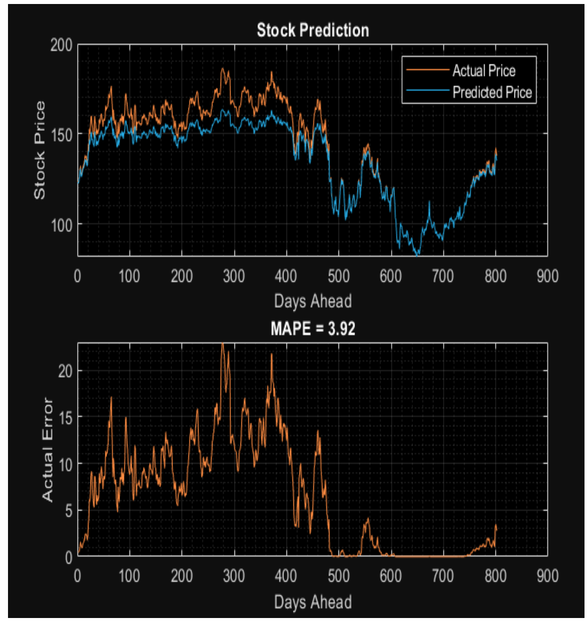


**Fig.4 Forecasting Results (Amazon)**

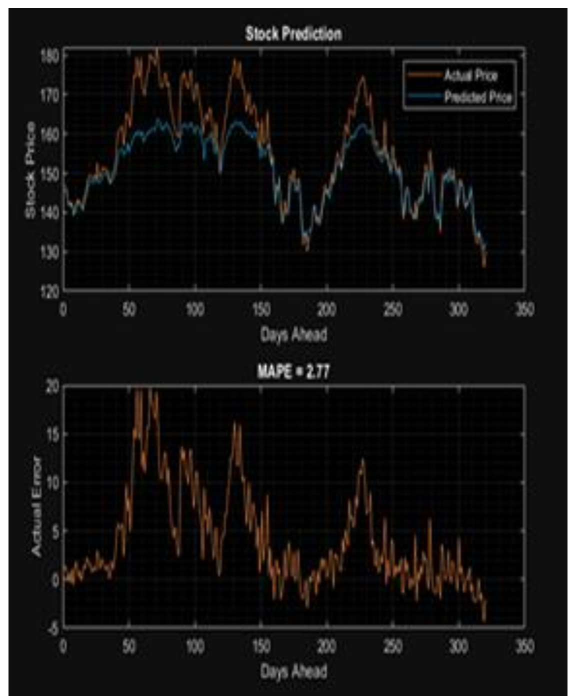


**Fig.5Forecasting: Dataset: (Tesla)**

The summary of results are presented in table 1.

**Table 1. Summary of Results:**

| S.No. | Parameter | Value |
|---|---|---|
| 1. | Dataset | Amazon, Tesla |
| 2. | Splitting Ratio | 70:30 |
| 3. | Pre-Processing | DWT |
| 4. | ML Model | Neural Nets |
| 5. | Regression Overall | 0.98 |
| 6. | %error (Amazon) | 3.92 |
| 7. | %error (Tesla) | 2.77 |
| 8. | %error [22] | 5.6 |
| 9. | %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 [22]., [23] in table 1.

## VII. CONCLUSION

A time series forecasting model of substantial significance to a wide range of stakeholders, including traders, investors, financial experts, and policymakers, is stock market forecasting. Stock market forecasting is necessary for a number of reasons. Stock market forecasts help investors make well-informed decisions about which stocks to purchase, hold, or sell. Precise projections have the potential to enhance portfolio optimisation and yield greater returns for investors. Businesses and individuals can evaluate and control the risks involved in stock market investments with the aid of forecasting. Implementing risk mitigation methods can be aided by having an understanding of future market changes. For numerous datasets, the suggested steepest descent method achieves a very low percentage error, demonstrating its great predicting accuracy. Furthermore, a comparison with previous research indicates that the suggested method outperforms baseline methods.

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