Amit Joshi, 18th July 1987, INDIA
Current position: Lecturer at ISMA University
University studies: BA School of business and Finance
Scientific interest: Artificial intelligence and machine learning, iOT
Publications (number or main): 6th
Experience: 14 + years

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MACHINE LEARNING BASED PREDICTION OF STOCK MARKET TRENDS

Priti Borda, Amit Joshi
ISMA University, Valērijas Seiles iela 1-korpuss 6, Rīga, LV-1019
**Corresponding author's e-mail: Pritiborda7@gmail.com*
www.isma.lv

Abstract

Forecasting results for stock markets exhibit variabilities in forecasting accuracy as the tenure of prediction is varied. Typically stocks are predicted for long, short as well as mid term tenures based on the tenure of prediction. While longer tenures have relatively much larger data to be trained as training data, divergences are also potentially large as the forecasting period may render higher randomness due to unprecedented events. The short term forecasting is relatively less prone to unprecedented events due to the tenure of forecasting. However, the lesser amount of training data may result in less accurate pattern recognition. A common ground is typically found in terms of mid term forecasting. This paper presents an experimental evaluation of all three formats of forecasting based on the training, testing split. The deep neural network model is used for the forecasting purpose and the forecasting MAPE and accuracy has been tabulated for a multitude of stocks. The comparative values of the MAPE for prediction have been tabulated to estimate prediction performance of the proposed approach.

Keywords: Stock Market Forecasting, Deep Neural Networks, Variable Forecasting Tenures, Forecasting MAPE, Forecasting Accuracy.

1 Introduction

Stock movement forecasting is a crucial aspect of financial markets and investment decision-making. Several factors contribute to the necessity and importance of predicting stock movements. Typically, financial markets are inherently volatile, influenced by a myriad of factors such as economic indicators, geopolitical events, and market sentiment [1]. Forecasting stock movements helps investors and traders navigate through this uncertainty, allowing them to make informed decisions and mitigate potential risks. Accurate stock movement forecasts are essential for effective risk management. Investors need to anticipate potential price fluctuations to implement strategies that protect their portfolios from adverse market conditions [2]. By understanding the potential risks, investors can make better-informed decisions about portfolio diversification and asset allocation. Investors rely on stock forecasts to make strategic investment decisions [3]. Whether it's choosing when to buy or sell a stock, enter or exit a market, or adjust portfolio holdings, accurate predictions enable investors to capitalize on opportunities and avoid losses. Timely and precise information is critical for optimizing investment strategies [4]. Forecasting stock movements aids in optimizing investment portfolios. By identifying trends and correlations, investors can adjust their portfolio mix to achieve a balance between risk and return. This optimization process involves considering factors such as asset class performance, sectoral trends, and the overall economic outlook. In today's digital age, algorithmic trading and automated systems heavily rely on stock movement forecasts [5]. These systems use historical data, technical indicators, and machine learning algorithms to predict future price movements. Investors and institutions use these automated tools to execute trades swiftly and efficiently. Typically, stock market forecasting can be categories based on the tenure of training and testing intervals [6]. Typically, the intervals defined are:

1) Short
2) Mid
3) Long

Sometime ultra short and ultra long term forecasts are also analyzed, though they are under the sub domain of short and ling term forecasts [7].

2 Influencing Factors

To incorporate global influencing factors, opinion mining and sentiment analysis has been extensively employed. Opinion mining, also known as sentiment analysis, involves analyzing public opinions, attitudes, and emotions expressed in textual data [8]. Applying opinion mining to stock market forecasting involves extracting sentiment from financial news, social media, and other sources to gauge investor sentiment and potential market trends. The first step in opinion mining for stock market forecasting is the collection of relevant textual data [9]. This data can include financial news articles, social media posts, analyst reports, and other sources. Text processing techniques, such as natural language processing (NLP), are then applied to preprocess and clean the data for sentiment analysis [10].

Opinion mining employs various sentiment analysis techniques to determine the sentiment expressed in the collected texts. These techniques may include rule-based methods, machine learning algorithms, and deep learning models [11]. The goal is to classify the sentiment as positive, negative, or neutral, providing insights into how the market participants perceive certain stocks or the overall market. Sentiment analysis generates sentiment scores that quantify the degree of positivity or negativity in the expressed opinions. These scores can be aggregated over time to create sentiment time series data. High positive sentiment may indicate bullish market expectations, while consistently negative sentiment could signal bearish sentiments among investors [12]. There are other associated challenges too while incorporating opinion mining or sentiment analysis metrics as governing factors, which can be summarized as:

It is very difficult to check the authenticity of the accounts or IDs from which the data is extracted. Lot of fake or dummy accounts are made.

Large biases are often found in such data making the parameter heavily biases and rendering inaccurate results in real cases.

Manipulated tweets or promotion based tweet (data) creating a wrong impact on the forecasting results.

Hence, this research tries to achieve high prediction accuracy even without the inclusion of the opinion parameter which not only eliminates the possibility of biased and fake data, but also reduces the rigour for data search.

3 Proposed Model

The methodology of the proposed approach can be thought of as an amalgamation of data pre-processing, feature selection and training using deep neural networks. Each of the sections have their own importance. The methodology is presented in each of the following heads which comprise the algorithm. The variation of the tenure of training and testing has been leveraged to forecast long, short and mid term movement [13].

Data Pre-Processing: The DWT:

Discrete Wavelet Transform (DWT) based filtering has gained attention in recent years as a powerful tool for signal processing, and it has found applications in stock market forecasting [14]. DWT is a mathematical tool that decomposes a time-series signal into different frequency components or scales. In the context of stock market data, this means breaking down the original time series into various frequency bands or levels. High-frequency components may capture short-term fluctuations, while low-frequency components represent longer-term trends [15]. DWT-based filtering allows for the separation of signal and noise components. By decomposing the stock market time series into different scales, it becomes possible to filter out high-frequency noise, which may be attributed to market volatility or irregularities [16]. This noise reduction helps in extracting meaningful features from the data that are more indicative of underlying market trends. The multi-resolution property of DWT enables the identification of trend and cyclical patterns in stock prices. Improved signal quality allows for more accurate modeling and prediction of future stock prices [17]. DWT-based filtering not only aids in forecasting stock prices but also contributes to risk management strategies. By identifying trends and patterns at different time scales, investors can make more informed decisions about when to enter or exit the market. Understanding the underlying structure of the data helps in managing investment risks effectively [18]. The DWT can be mathematically expressed as [19]:

$$\boldsymbol{F(x,y)} \xrightarrow[\boldsymbol{DWT2}]{} \boldsymbol{C_A, C_D, C_H, C_V} \tag{1}$$

Here,
$C_A$represents the approximate co-efficient values.
$C_D$represents the detailed co-efficient values.
$C_V$represents the vertical co-efficient values.
$C_H$represents the horizontal co-efficient values.
$DWT2$represents the discrete wavelet transform on the actual data.

The idea is to keep the C_A values while removing the C_D values so that the data can be filtered. The filtered data is then applied to the deep neural network model.

Moving Window:

To sample the recent trends in the data, a two way moving filter based windowing has been employed in this work which captures the recent $(l - m)\ samples$ of the data. This is fed as an additional sliding input to the training vector:

$$\boldsymbol{\frac{n}{2} \leq k \leq n} \tag{2}$$

Here,
n is the number of samples for forecasting.
k is the length of the sliding window.

We also introduce an additional parameter, r_k, in the range $k\epsilon[\frac{n}{2}, n]$, such that,

$$\boldsymbol{r_k = \frac{\partial y(n,k)}{\partial n}\ \forall k\epsilon[\frac{n}{2}, n]} \tag{3}$$

Here
r_k signifies the rate of change of the target in the sliding interval of $[\frac{n}{2}, n]$.

Deep Neural Network Model for Pattern Recognition:

Several approaches have been explored to forecast stock trends accurately but one of the most effective techniques happens to be the deep neural network model. The algorithm proposed in this approach aims to reduce the swing or overshoot of the training algorithm while attaining convergence [19].

The proposed algorithm is presented next:

Algorithm

The algorithm of the proposed approach is presented subsequently:

Step.1 *Divide the data for training and testing*
Step.2 *Apply DWT to filter data by keeping CA values while removing the CD values.*
Step.3 *Apply dual averaging window of*

$$(l - m) \text{ and samples and } \frac{\partial y(n,k)}{\partial n} \ \forall \ k \ \epsilon.$$

Step.4 *To train the network, employ the following training rule:*

$$\boldsymbol{v_a \partial w = m v_a \partial w + (1 - m) \partial w} \quad (4)$$

Here,
v_a represents the learning velocity along 'a'.
m represents the momentum factor
w represents the weights.
∂w represents the differential weights

Step. *5 If (MSE is stable for multiple iterations)*
Stop training process
else if (exhausted max. iterations)
Stop training process
else
Feedback the errors of prediction and adjust weights accordingly.
Step. 6: *Vary the training testing tenure for prediction to estimate variable period prediction.*
Step.8 *Compute performance metrics.*
The experimental results are presented subsequently.

4 Experimental Results

The data collected is from Yahoo Finance for Tesla stocks. The experimental results have been presented in this section with variations in the forecasting samples so as to incorporate long, mid and short term forecasting. The Tesla stocks over a ten year period has been used for evaluating the performance of the proposed algorithm. A similar approach can be employed for all the other stocks.

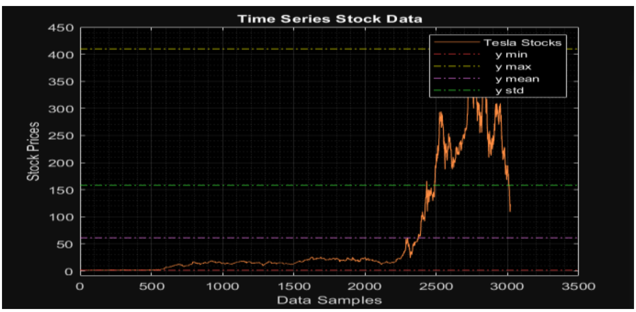

Figure 1. Statistical Features of Raw Data

Figure 1 depicts the variability of the raw data.

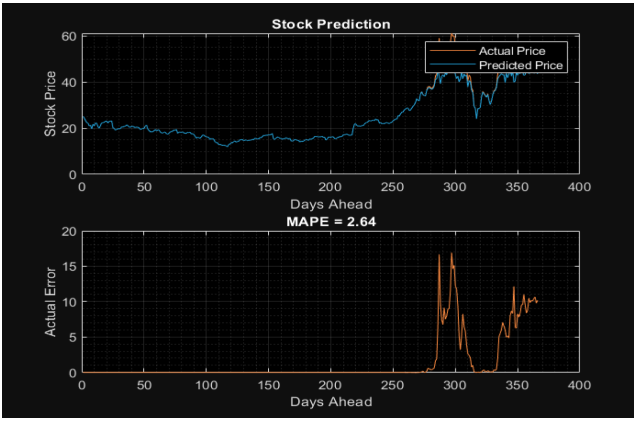

Figure 2. Long Term Forecast

Figure 2 presents the MAPE results for the Tesla stocks over a period of 1 year. It can be observed that the MAPE is 2.64%.

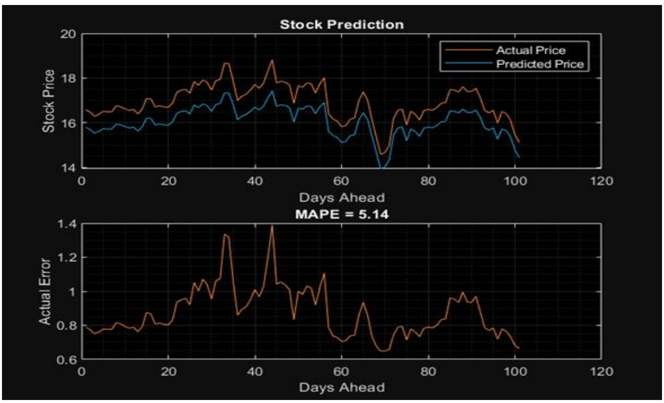

Figure 3. Mid term forecast

A similar prediction for a tenure of 100 days renders the perdition MAPE of 5.14%

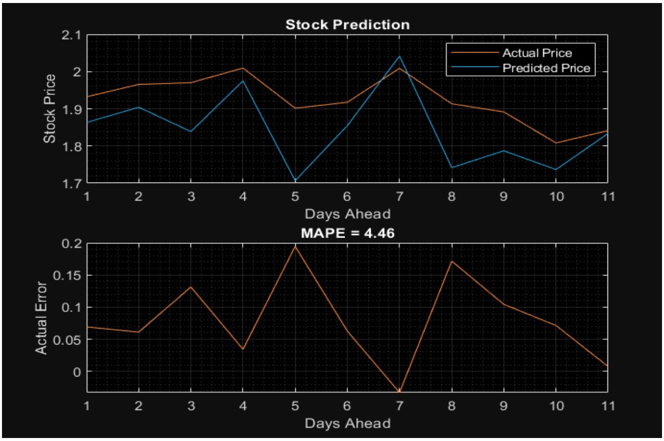

Figure 4 Short term forecast

The prediction for a tenure of 10 days (short term) renders the perdition MAPE of 4.46%

Table 1

Perdition MAPE values obtained

S.No.	Duration	Days Ahead	MAPE	Accuracy%
1	Long Term	365	2..64 %	97.36%
2	Mid Term	100	5.14 %	94.86%
3	Short Term	10	4.46 %	95.54%
4.	Mean MAPE		3%	97%

The comparative analysis of the MAPE for all the 3 forecasting models indicate the following:

1) The long term forecast yields the minimum MAPE thereby rendering maximum accuracy of forecasting, for the Tesla stocks.

2) The mid term forecast attains the maximum MAPE thereby rendering the minimum accuracy for the Tesla stocks.

3) Short term forecasting attains slightly lower MAPE than mid-term forecasting for the Tesla stocks.

Table 2

Comparison with Previous Work

S. No.	Authors	Approach	MAPE
1.	Kim et al. [20]	Transfer Entropy Augmented Feature Learning	43%
2.	Li et al. [21]	LSTM with Sentiment Analysis	51.4%
3.	Althelaya et al. [22]	EWT with Stacked LSTM SWT with Stacked LSTM	5.548% 12.888%
4.	Gao et al. [23]	Genetic Algorithm with Multi Branch CNN (GA-MBCNN)	17% (best case)
5.	Subbakar et al. [24]	ARIMA	14%
6.	Gulmez et al. [25]	Rabbits Optimization with LSTM	6.58%
7	Ray et al. [26]	BERT-LSTM GRU TCN Deep transformer MB-TCN	28% 26% 20% 18% 16%
8.	Zhan et al. [27]	Sliding Window with LSTM	5.61% (best case)
9.	Proposed Approach	Back Propagation Based Gradient Descent	3% (mean)

A comparison with existing approaches such as Effective Transfer Entropy [20], LSTM combined with Sentiment Analysis [21], Empirical Wavelet Transform (EWT) with LSTM [22], GA with MBCNN [23], ARIMA [24]GA-SLTM and GA-ARO [25], BERT-LSTM, GRU, TCN, Deep Transformer, MB-TCN [26] and Sliding Window with LSTM [27] based models. Thus the proposed approach outperforms baseline approaches in terms of the mean absolute percentage error (MAPE). The concluding remarks pertaining to the obtained results have been presented next.

7 Conclusions

This paper presents a DWT-Neural Network based approach for forecasting stock trends over a varied interval period. The categorization of the forecasting has been done based on the number of samples ahead in forecasting. A 365, 100 and 10 day split has been chosen for the long, mid and short term forecasts respectively. An illustration analysis has been made for the Tesla stocks over the variable forecasting period. The prediction MAPE analysis shows that the accuracy achieved is 97.36%, 94.86% and 95.54% for long, mid and short term forecasts respectively, with a mean MAPE of 3% across all intervals of forecast. The model also attains an MAPE of around 3% across various stocks for benchmark S&P 500 dataset obtained from Yahoo Finance. Low values of the MAPE ascertains accurate prediction of the stock trends.

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Authors

Priti Borda, 10/04/1998, INDIA
Current position, grades: Junior sale consultant at European solution
University studies: Master in Computer Systems
Scientific interest: Artificial Intelligence and Machine Learning
Publications (number or main): main
Experience:

Amit Joshi, 18th July 1987, INDIA
Current position: Lecturer at ISMA University
University studies: BA School of business and Finance
Scientific interest: Artificial intelligence and machine learning, iOT
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