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Predicting Stock Price Movement Using Sentiment Analysis and CandleStick Chart Representation

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Abstract: Predicting stock price movement is an important topic of academic interest. Due to challenges of traditional methods in predicting stock price movement perdition we address this challenge by using machine learning which can use valuable near real-time information from social media platforms. We investigate whether models using machine learning algorithms can predict stock price movement with accuracy. We developed a comprehensive machine learning model and validated with real-world application using data collected from Yahoo Finance on five high-demand stocks from the United States: Apple, Tesla, IBM, Amazon, and Google. An experiment of deep neural network implementation in the stock investment comprises technical indicators, sentiment, and candlestick to predict the stock price. Using Twitter data, we offer a sentiment analysis and time series data transformed into the candlestick chart so that patterns can be elucidated. The step is followed in the candlestick chart for the prediction of stock price for a period of 10-days. We achieve the most favourable performance on AAPL stock with 75.38% accuracy over 10-day period and less favourable performance for the IBM stock with 51.26% accuracy over a period of 4 days. Also, our model was able to achieve the most balanced results for TSLA stock with 79.59% recall, 71.86% accuracy, 73.58% F-score and 68.42% precision over a period of 10-days. We demonstrate operational value of deep learning approach by showing that stock price movement can be predicted over a short period by using Twitter data, considering multichannel collaborative network, candlestick chart as well as sentiment analysis.

Keywords: stock price prediction; machine learning, deep learning neural network; sentiment analysis; candlestick chart; Twitter.

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1. Introduction

There is an increasing interest in approaches for predicting movement in the stock market and, more importantly, to understand reasons based on different scenarios and possibilities of stock price movement (Hasan et al., 2021; Mund et al., 2020). Investors and financial analysts look for the stock price prediction for their investments and it is one of their subjects of interest. It is very difficult for the investor to predict the best time to buy or sell a stock because many factors influence the price movement of stocks. The efficient market hypothesis highlights that stock prices cannot be predicted and investing in the stock market is subject to risk. However, when investing, investors always look for indicators for stock price movement so that they can take the advantage of buying the most underrated stocks or selling the overrated stocks (Malkiel & Fama, 1970). Market sensitive news such as the performance of the company, investor sentiments, economic and environmental variables, brand capital, competitive pressure, and stakeholder relationships variables in the prediction model play crucial roles in determining the stock price and future trends (Bharati & Geeta, 2017;

Cen et al., 2016; Cuculiza et al., 2021; Hasan et al., 2021; Li & Zhan, 2019; Vitorino, 2014). On the other hand, the stock market instability due to recent Covid-19 pandemic and recent geological uncertainty signify the importance of understanding predictors of stock price for investors and fund managers (Hasan et al., 2021). Thus, prediction of stock price movement with reasonable predicting validity based-on real time or near real-time information from non-traditional sources may yield higher profits for investors and fund managers.

A stream of empirical research has demonstrated that traditional methods (Balcaen & Ooghe, 2006; Jackson & Wood, 2013) such as sophisticated regression and random walk models are not able to generate accurate prediction of stock price (Bradshaw et al., 2012; Harvey et al., 2016; Hou et al., 2020; Monahan, 2017). The results of regression analysis and random walk methods can be problematic for generating theoretical perspectives and practical insights (Anand et al., 2019). To address this issue and to overcome failures of regression analysis and random walk methods new research warranted to examine the availability and application of methods based on emerging technologies and moving the accounting research front forward (Balcaen & Ooghe, 2016; Beattie, 2005; van der Heijden, 2022). Whilst Hasan et al. (2021) demonstrated that advanced machine learning approach can predict future stock price crashes, Huang et al. (2015) show how sentiment analysis of investors can be a powerful tool of predicting stock return. Avramov and Metzker (2021) argue that machine learning methods could indicate a promising direction to identify mispricing when trading frictions attenuate because of their advanced mechanism of aggregating individual anomalies.

A stream of empirical research has demonstrated that predicting stock price of firms with reasonable accuracy is one of the fundamental albeit challenging analytic tasks for investors as well as for fund managers. Recent work shows that due to advances artificial intelligence, machine learning, deep learning can help to improve the model which can be applied to predict stock movement with a reasonable degree of forecasting. Recent studies show the predictive modelling power of machine learning reduces out-of-sample prediction error as well as offers insightful incremental information based on higher prediction validity (Hasan et al., 2021; Jones, 2017). Machine learning offers opportunity to collect information in a naturalistic way which accommodate efficient and effective predictor to mitigate biases, uncover hidden patterns and relationship in the unstructured data (Avramov et al., 2021). In this paper we apply a new approach combining sentiment analysis and candlestick chart representation of Twitter data. We develop several approaches for predicting short-term stock price movement using various multichannel collaborative network, candlestick chart, and sentiment analysis of Twitter data and compare their performance in prediction of stock price movement. We argue that this approach will provide several useful approaches to the investors in stock market who are particularly interested in short-term return on investment.

To book high profits, the stock trader must focus on the evaluation of the performance of the company before purchasing the stock. In the recent past, deep learning technology, especially the convolutional neural network, has attracted many investors because of its favourable performance in the research field (Lu et al., 2021). Deep learning technology has been applied by many researchers for stock market prediction. Stock market prediction can be done by several approaches and analysing the indicators of historical time series data is one such approach (Chen et al, 2018). Apart from this one can also look at social media and analyse the financial news for stock market prediction (Chen et al., 2017). To enhance the prediction accuracy of the classifiers, there can be a combination of different classifiers with the help of simple methods in machine learning. The study has highlighted the novel framework used for the prediction of the stock market that uses candlestick (Hung & Chen, 2021) and sentiment analysis of the social media data (Mehta et al, 2021). There is very little research available that incorporates candlestick charts and data from Twitter to predict the price of the stock (Ho & Huang, 2021).

One of the most popular tasks for the natural language processing area is the classification of sentiment which aims to predict the sentiment from the text (Xu, 2020). Social media is flooded with the comments and opinions of the public which can be easily shared by others. There are many levels on which the sentiment classification can be done; they are word phrase/ label, sentence label, and document label (Bharati and Geeta, 2017). For accepting sentiments enterprises from the various online sources one of the most popular approaches is sentiment analysis.

This research paper discusses how the passion and enthusiasm for stock trading are not diminished even after the advancement in technology and development in the economy of the world. The past hundred years have seen the publication of a lot of books from successful investors to highlight the taste of investment success (Nti et al., 2019). Countless papers have been published on the stock markets that have expressed views on how to make a consistent profit from the stock market. Most of the research paper has given efforts into the stock market but how to predict the stock market's future and make an optimum profit is not discussed in the paper. This paper has highlighted that the reality is very discouraging as most of the investors lose their money in the long run and only 10 per cent of investors can make a profit in the stock market (Chen et al, 2018).

The social media data is derived from the text data that comes from the tweet whereas the candlestick charts of the data consist of colour images hence instruction of information is required as well as processing is necessary before it is incorporated into the collaborative network. Apart from this, the natural language toolkit is used for social media data for the sake of sentiment analysis of the content(Mehta, et al., 2021). The spam and irrelevant information have been removed so that the model achieves proper sentiment score features. The "mpl_finance" module has generated the candlestick chart data with the help of four features: they are open, high, low, and close to the historical time series data(dgoldfarb, 2020). Apart from this, the candlestick chart has helped with the data, and it was normalized before it was incorporated into the collaborative network for the extraction of the features(LIN, et al., 2021). Moreover, to incorporate features on social media as well as candlestick chart data, a multi-branch network was designed. Thus, the motivation of this study is (1) in predicting stock price movement using traditional models machine learning and deep neural network (DNN) and comparing between those models, (2) and determining the candlestick charting and explore it works with the DNN model. This study further encourages to utilise the data that are available to study the relationship between the technical and sentiment analysis as well as the movement of the future stock market.

We developed a comprehensive machine learning algorithm using historical data collected from Yahoo Finance, candlestick charts, and social media data to predict the stock price movement of five high-demand stocks from the United States: Apple (AAPL), Tesla (TSLA), IBM (IBM), Amazon (AMZN), and (GOOG). This study applies deep neural network implementation in the stock investment which comprises technical indicators, sentiment, and candlestick to predict the stock price movement. By extracting information from social media platform Twitter, this study offers a sentiment analysis of social media data. The data used in this study include the historical time series data of the stock is transformed into the candlestick chart so that patterns can be elucidated in the movement of the stock. The step is followed by the integration of the stocks in features as well as the candlestick chart for the prediction of the movement of the stock for a period of a maximum 10 days.

Our model was able to successfully achieve the most favourable performance on AAPL stock with 75.38% accuracy over a 10-day time. On the contrary, the least favourable performance was achieved in the IBM stock with 51.26% accuracy over a period of 4 days. Also, our model was able to achieve the most balanced results for TSLA stock with 79.59% recall, 71.86% accuracy, 73.58% F-score and 68.42% precision over a period of 10-days. Our results provide support for the role that ML-based approaches can play in predict stock price movement with high accuracy over a short-period.

This paper contributes to the accounting and finance literature of predicting stock price movement considering multichannel collaborative network, candlestick chart as well as sentiment analysis of the data from Twitter for the prediction of the stock. *First,* the stock movement prediction plays a crucial role in determining the ups and downs of the stocks in the future compared with the price prediction at the time of market close (Chakraborty et al., 2017). The public sentiment (Nti et al., 2019) and technical analysis (Xu & Cohen, 2018) have been considerably popular methods for predicting the movement of stock prices in the market, which has become a key area for research. However, very few studies have been considered using the combination of public sentiment and technical analysis to predict stock prices movement. *Second,* several studies are researching the prediction of the stock market with the help of sentiment analysis using the traditional methods (Bharati and Geeta, 2017). However, this study contributes to the development of technology, has helped in the progress made in machine learning and encouraged meaningful researchers to come up with a different perspective on the aspect. *Third,* artificial intelligence has significantly evolved from multilayer perception (Chakraborty et al., 2017), applying Twitter sentiment to predict stock movement. In contrast, Chen et al. (2015) have used LSTM and primary stock market data, including OCHL data, to predict the stock market and improve over the old methods. On the other hand, there has been an experiment by Nelson et al. (2017) on the technical indicators of stock and LSTM that has been derived from OCHL that is better than the traditional methods with few limitations. Following this prior literature, this study contributes a deep neural network that considers the following factors: stock technical indicators, sentiment, and candlestick to predict the stock. *Fourth,* the paper has also discussed the Japanese candlestick charting and how it is different from financial tweets in stock technical indicators in determining the movement of the stock (Ho & Huang, 2021). *Finally,* the research experiment has contributed to popular candlestick patterns that encourage to developing a DNA model that uses candlestick charting for the data source.

2. Literature Review

2.1. Predicting Stick Price

There is no doubt in the fact that forecasting of stock is one of the challenging tasks because of the nonlinear and chaotic financial characteristics. Different additional methods are used to guide the investment in stocks. The two groups of prediction methods are technical analysis and fundamental analysis that is used as an analysis in the investment in the stock market(Nti, et al., 2019). The fundamental analysis deals with the concerns of the company by considering the economy of the firm, employees, annual reports, and financial status., whereas the technical analysis looks at the historical data for future stock prediction(LIN, et al., 2021). Technical analysis helps the investor to build profitable trading strategies. The utilization of candlestick charting, and open high low close is very helpful in predicting the stocks as it not only depicts the fluctuating balance between the demand and supply, but it can also perform the sentiment analysis of the investors in the market(Bharathi & Geetha, 2017).

The future value of the stock of a company can be determined by stock market forecasting. Social media like Twitter, Facebook, and other platforms such as websites and blogs are flooded with information describing the financial market condition(Bharathi & Geetha, 2017). The two factors on which the price of a stock depends are the fundamental factor and the technical factor. The statistical data of an organization is known as the fundamental factor and it comprises reports, the financial status of the organization, the balance sheet, various policies of the company, and the dividends. On the other hand, the technical factor mainly depends on the trend indicator, the ups, downs, low values of the day stock, volume increases extra. Traditionally people used to download the historical price of the specified company from the website(Ho & Huang, 2021). To compute the value of the stock there are various stock level indicators. Some of the stock level indicators that are popular among readers are Bollinger bands, typical point, moving average, accumulation distribution, stochastic RSI, and many more.

More than 65% of the stock market prediction documents were completely based on technical analysis (Nti, et al., 2019). Initially, the technical analysis was done using the candlestick charting performing statistical analysis from the past data to know about the prediction and it was limited to such parameters only. (Chen, et al.,

2016) explains the quantitative definitions of the four pairs of the candlestick pattern to learn the predictive power in the stock market of China. The researchers have come up with the result that highlighted the two-day candlestick pattern has various predictive capabilities. On the other hand, another author came up with the statistical test that comprises 8 kinds of three-day patterns and identified the candlestick patterns that consist of predictive power(Caginalp & Laurent, 1998). (Lu, et al., 2015) examined the 8-day patterns and used three definitions of trend as well as four holding strategies in the DJIA component data. The research came up with the conclusion that regardless of the definition of the trade that was involved, the pattern with the Caginalp-Laurent holding strategy was pretty much profitable(Lu, et al., 2015).

The dividends that are provided by the company help the investor to gain significant profits moreover they can also purchase new stocks easily. The company bonus programs for the stakeholders help the investor to get significant profits from the dividends. Apart from this, the investor can deal their stocks with the other traders in the market through the stock brokerage and the trading platforms that are available electronically(Ho & Huang, 2021). The investors can seek help from stock traders that would increase in the future and sell those stocks that would decrease due to poor performance. Hence, the stock trader must have enough knowledge to predict the future of the stock properly so that the investor can earn more profit in the stock. The paper has discussed the development of an automatic algorithm that can predict the change of the market so that it helps the trader to get the maximum benefit.

Lin et al. (2021) has discussed many algorithms of data mining that would help in the prediction of stock price. The opinion summary is completely based on the opinion sentences. One upon reading the paper will get to know the information and why it is not helpful for the opinion-based summary (Balahur, et al., 2012). To get rid of the complex space modelling of the different sources, the paper has seen the introduction of a tensor-based information framework that would help in the prediction of stock price (Li, et al., 2016). The framework was thought to be generalizable when compared to other multidimensional learning problems and it does not emphasize the interaction of time. The predictive power of the single-day candlestick charting was experimented with by (Lu, 2014) with the help of daily data taken from the Taiwan stock market from the period of 4 January 1992 to 31st December 2009. The result has shown that the patterns were pretty much profitable for the stock market of Taiwan even after the transaction cost.

Mood tracking tools are useful in analysing the daily text content in social media platforms such as Twitter. The daily text is also investigated for the prediction of the changes of DJIA closing values. The DJIA closures are based on the self-organizing fuzzy neural network(Zhang, et al., 2020). This approach has a lot of resemblance with the approach of mood tracking. To forecast fuzzy time series, the implementation of a back-propagation neural network using technical indicators was used. According to the study, the researchers had observed that the ANN is more efficient in forecasting ability than the time series model.

With the help of public moods, the prediction of the Chinese stock market has been extracted from microblog feeds(Yan, et al., 2016). To predict the stock market price index, a detailed description of the input variables was also considered. Different Artificial Neural Networks (ANN) models were implemented for predicting and comparing the results (Enyindah & Uzochukwu, 2016). It was found that Non-linear forecasting neural networks delivered good results.

2.2. Sentiment Analysis in Stock Market

The last ten years have seen the massive importance of sentiment analysis as it helps to get a large amount of digital data on the news as well as social media platforms. People have seen a dramatic improvement in communication due to the development of social media in the last decade. Social media companies such as Facebook and Twitter have received millions of active users. This has given the consumers to share information and apart from this the information spreader much faster than the traditional media(Xu, 2020).

The platforms are flooded with enormous data and this has helped the researchers to explore big data like the behavior of the user and the sentiment of the public.

One of the best examples of how we are getting influenced by social media is when Twitter was used by the President to declare the policies. The 40th President of the United States of America Donald Trump was elected in the year 2016 and where he discussed the importance of social media in his daily life(Bharathi & Geetha, 2017). Since 2016, social media platforms play a crucial role in getting information about anything. Over time, the platforms have a major role to play in every aspect of our personal life whether it is in technology, economy, or politics. A recent report of CNBC has highlighted that in 2016, days with more than 35 tweets created by Donald Trump have given negative returns of -9bp. However, in the days where there were fewer tweets than were 5 tweets, the stock market has seen positive returns (+5bp)(CNBC, 2019).

Previous research discussed the usage of Twitter mood in early research to detect the stock market compared to the non-sentiment method. Research has been carried out on the mining opinions of the users for various application areas(Al Amrani, et al., 2018). A Google Profile of Mood States (GPMS) was built by (Karlemstrand & Leckstr¨om, 2021) to categorize the tweet sentiment into different emotions. It was found that compared to the general levels of Option Finder, the sentiments of Happiness and Calm yielded better predictive power. Lately, (Pagolu, et al., 2016) also came up with the conclusion of correlation between public sentiments into the tweet as well as stock future movement.

Apart from this, (Li, et al., 2020) performed a bidirectional emotional recurrent unit for figuring out the emotion in the conversation. Some researchers also started to make use of sentiment analysis with the help of the same trend for the stock prediction to determine the movement of stock. Ali et al. carried out sentiment analysis to determine the transportation entities in the huge Corpus and to figure out traffic accidents to minimize serious injuries (Ali, et al., 2021). (Khan, et al., 2020) used algorithms on financial news data as well as social media to explore the influence of data on the movement of stocks. Another researcher, (Ho & Huang, 2021) performed a sentiment analysis to determine the movement of the Dow Jones Industrial Average (DJIA) stock market surrounding microblogging site Twitter. (Basiri, et al., 2021) also came up with the sentiment analysis method on the social media platform of Twitter data set with the help of the attention-based bidirectional CNN-RNN Deep model. The correlation between the sentiment of the text and the stock twist website comments has been explored by (Khatri & Srivastava, 2016) and the prediction of stocks price from Facebook, Apple, Google Oracle, and Microsoft has also been done for sentiment classification. The SVM classifier was utilized by (Chakraborty, et al., 2017) and the prediction of stock movement was done by the application of the boosted regression tree. It has been seen that the problem in utilizing Twitter for predicting stocks is because it is a general social network and there are different sources to provide information on this platform. The statistics of information of the pointless tweets states that it is not fake or misleading information, but they are categorized as widespread on Twitter(Xu, 2020). Therefore, it is doubtful whether the tweeter can be regarded as a reliable source for the financial market or not.

2.3 Deep Learning in Finance

A lot of efforts have been made by the researchers to have an overview of the application of deep neural networks. (Lee, et al., 2021) has discussed how the NN model including feature engineering and technical analysis has helped the investor to make proper selling decisions and minimize the loss but the investors fail to make higher profits in buying decisions with the help of the proposed model. (Shen & Shafiq, 2020) utilized a modular neural network to detect the stock exchange in Tokyo as well as the internal representation of the Tokyo stock exchange index. Tokyo Stock Exchange System has got accurate predictions and it also received considerable profit. The reaction system offers both buy and sell signals so that the investor benefited from making rapid trading decisions. In various time series data issues like Natural Language Processing and Speech Recognition, the implementation of Recurrent Neural Networks was done. But there were problems such as exploding gradient (Philipp, et al., 2017) and vanishing gradient (Hu, et al., 2021) that has created difficulty to educate the RNN models on various time steps. The LSTM approach has helped in finding a solution to various tasks that were difficult to solve with the help of previous algorithms for RNNS(Karevan & Suykens, 2020).

2.4 Candlestick Charting

In early 1700, the Japanese Candlestick Chart was developed so that rice prices can be predicted. In the book of Nison, one can see the uses of the tool and how the patterns can help in detecting the stock movement (Nison, 2001). A study by (Lin, et al., 2021) has revealed the predictive power of the candlestick pattern as well as the combination of the candlestick patterns with various technical indicators to get profitable returns. Apart from this, (Yassini, et al., 2019) also analyzed Dow Jones Industrial Average (DJIA) data and concluded that the candlestick technical analysis is not helpful in the stock market of the US. Moreover, (Zhu, et al., 2016) have explained the benefit of the five different candlestick reversal patterns in the stock market of China. According to statistical analysis, it can be concluded that bearish harami and crossed signals are good performers in predicting reversals for the stocks that have low liquidity. On the other hand, bullish engulfing and piercing patterns are pretty much profitable when implemented in highly liquid small company stocks. Thammakesorn and Sornil (2019) explored the Japanese candlesticks of technical analysis of more than 300 stocks and came up with the conclusion that Doji, crow, and stars patterns do not help predict the movement of the stock. To approach the stock data, different methods have been found by researchers and the historical time series was transformed into other forms so that the various patterns in the stock movement can be learned easily. (do Prado, et al., 2013) took the help of 16 candlestick patterns to come up with the stock movement for Brazil and another researcher combined the candlestick chart with 7 wavelet-based textures to forecast the stock movement(Tsai & Quan, 2014).

3. Data and Methods

3.1. Data

The project aims to follow live tweets from twitter and predicts the stock prices. The purpose of the study is to create an intelligent stock trading Bot that can help in making intelligent decisions with the help of supervised machine learning, NLP and sentiment analysis of twitter data for enticing people's opinion about the particular stocks that people are currently talking about.

3.2 Method Moving Average Method Stock Level Indicators

Moving Average is a tool for performing technical analysis where the actual index data is compared to the average of a specific period(Bharathi & Geetha, 2017). Simple Moving Average (SMA), Weighted Moving Average (WMA), and Exponential Moving Average (EMA) are the three types of moving average. The common periods considered for moving the average of stocks are five days, ten days, fifteen days, twenty-one days, fifty days, hundred days, and two-hundred days.

The moving average stock level indicator is widely used as it helps to reduce the noise on the price chart when compared to other indicators, thereby, offering a smoothed line.

The market sentiments are determined using Sensex. 30 prominent stocks obtained from key fields in Sensex are actively traded in the Exchange. This includes well-established and financially strong companies from different fields. To predict if the next day's Sensex will rise or fall, the moving average is applied to the Sensex data. Usually, the Sensex is calculated by using Equation 1.

$$Sensex = \left(\frac{sum\ of\ free\ float\ market\ capitalization}{Base\ Market\ Capital}\right)100 \quad (1)$$

The capitalization of free-float market can be done by using Equation 2.

$$Free\ Float\ Market\ capitalization\ = Share\ price(shares\ out\ standing - locked\ in\ share) \quad (2)$$

To calculate the moving average of a particular stock, the addition of closing price and dividing the sum by the total number of periods is done. Moving Average is applied by using Equation 3.

$$F_t = \frac{A_{t-1}+A_{t-2}+A_{t-3}+\cdots+A_{t-n}}{n} \quad (3)$$

F_t = Forecast for the coming period,
A_{t-1} = Actual occurrence in the past period for up to 'n' periods,
N = Number of periods to be averaged.

The predictive system has come up with a moving average for 5 days, 10 days, and 15 respectively. A comparison has been performed below.

If in case, the five days is more than 10 days and the 10 day is more than 15 days, then one can determine that outcome is positive, and the index would go up on the very next day. However, if the vice versa happens that the 5 days is less than the 10 days and the 10 days is not more than 15 days then the negative would happen, and Sensex would go down the next day. The result is neutral and there is no change in Sensex when the five day is less than 10 day, and the 10 day is more than 15 day and also when 5-day is more than 10-day and 10-day is less than 15-day.

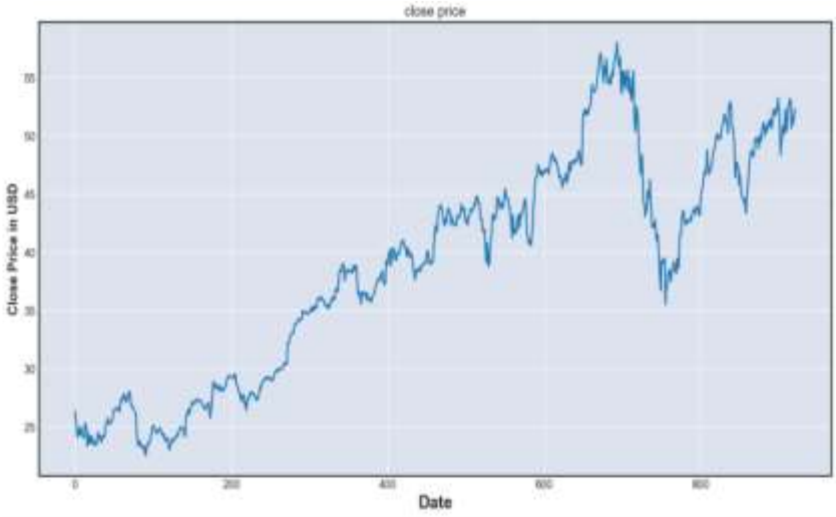
4. Results and Data Analysis

The data collection, as well as processing procedures, will be discussed in this section initially. The enhancement in the field of sentiment analysis that has been achieved through CNN will also be discussed. After this, the explanation of the improvement in the joint network with the evaluation of the various aspects of the prediction of the stock price movement as well as a discussion of the various trends of stocks in different time intervals will also be seen here.

4.1. Historical data from Yahoo finance

In the United States, there were five high-demand stocks selected which were Apple (AAPL), Tesla (TSLA), IBM (IBM), Amazon (AMZN) as well as Google (GOOG). There were a variety of factors on which the stocks were chosen and one of the major factors is the market capitalization of the stocks as well as the popularity of the stocks in the global market and institutional investors. The finance API was collected from Yahoo where the historical time series data were selected from every stock. The date, open, high, Low, volume as well as the stock open price are some of the features that have been extracted. The stock price and future trends were found in the next 4, 6, 8, and 10 days. For testing, 20% of the data were kept by the researcher and the rest of the data were kept for the training from the stock data.

Figure 1: Illustration of Candlestick data for stock price movement prediction



4.2. Sentiment data from social media

The scrape library for the tweet collection from the Twitter social media platform for the selected stock and this library have assisted in scraping tweets without the limitation of Tweepy. For social networking services, the Snscrape is a scraper. The scraper is useful in scrapping items such as profiles, hashtags, searches, and lastly, it also helps in returning the discovered items, for example, relevant posts(Chakraborty, et al., 2017). The input parameter is obtained by the python application for an example search query, symbols of the chosen stock, the start date as well as the end date. The tweets of the particular store downloaded in Adobe format during a specific period. There are four features of the tweet data they are date, TweetText, retweet count, and like count. This feature helps indicate the date when the tweet was posted and the content of the tweet. Apart from this, it can also express the number of retweets and the number of likes on a particular post.

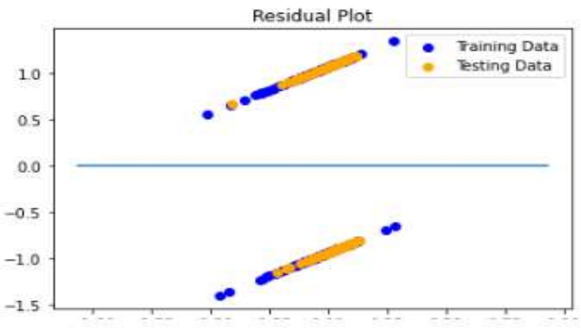
4.3. From Historical Data to Candlestick Chart

Open, high, low, and close which is known as OHLC are the full features of the candlestick chart. The" mpl_finance" module is used to create the candlestick chart that contains the new matplotlib. Finance API which makes creation of financial plots easier. The below figure depicts an example of candlestick chart data.

Figure 2: Illustration of data for stock price close price prediction

Date	Open	High	Low	Close	Candlestick chart
2016-06-30	23.61	23.94	23.56	23.90	
2016-07-01	23.87	24.12	23.83	23.97	
2016-07-05	23.85	23.85	23.61	23.75	
2016-07-06	23.65	23.92	23.59	23.88	
2016-07-07	23.92	24.13	23.91	23.99	

Figure 3: Illustration of the predicted the stock prices for a given range of the date



4.4. Experimental Setting

There are full of hyperparameters in the Deep learning models and hence it becomes a very time-consuming process in finding the potential configuration in the CNN model. Apart from this, it also becomes a resource-consuming process. To evaluate the optimal values of the hyperparameters, the proposed work has been done with the help of some procedures so that a high-performance model can be achieved. All these hyperparameters were the optimizer function batch size as well as the learning rate. From the scikit-learn wrapper class, a GridSearchCV approach was implemented in the Keras API so that optimal batch size could be identified and the optimizer function. The grid search of the batch size was defined in the set of (8, 16, and 24) as well as the optimizer function in the form of Adam, SGD as well as RMSprop. For each combination of these parameters, the GridSearchCV was constructed and then evaluated by using three-fold cross-validation. Later, Reduce LROnPlateau and Modelcheckpoint callbacks API were applied in the Keras to control the learning rate and save the best model. If no improvement was found after 20 continuous epochs, the learning rate would be reduced by a factor of 0.5. The process was performed until the lower bound was achieved. The lower bound on the learning rat was set 0.0001 and the coarse learning rate was set 0.001. As per the validation loss value at every epoch, the Modelcheckpoint stored the best model.

4.5. Improvement in Stock Trend Prediction based on Sentiment Analysis and 1D-CNN

To come up with a potential stock trend prediction model based on sentiment analysis, the research has conducted experiments with the help of 5 methods that have been discussed above. To predict the trend of the stock for the five high-demand stocks, each method was implemented over different periods that are 4 days, 6 days, 8 days, and 10 days. To mark the highest accuracy of the stock, it was highlighted in bold and below table has highlighted the 1D-CNN model achieved better performance than the Random Forest, Linear SVM, and LSTM models in most of the situations. 71.36% was the highest accuracy achieved on AAPL stock with the help of the 1D CNN model. However, for the IBM stock, the percentage was as low as 46.73% in the prediction of the subsequent 4 days with the help of the RF classifier. Hence for sentiment analysis of the stock in prediction, the utilization of 1D-CNN has been used.

Table 1: Accuracy improvement of stock trend prediction based on sentiment analysis and 1D-CNN

Stock	Time Period	RF	LinearSVC	GaussianNB	LSTM	1D-CNN
AAPL	10 days	62.81%	51.76%	58.79%	62.81%	**71.36%**
	8 days	61.31%	56.28%	60.30%	60.30%	**71.86%**
	6 days	56.78%	55.28%	59.30%	57.29%	**65.33%**
	4 days	61.31%	51.76%	55.28%	60.80%	**67.84%**
TSLA	10 days	60.80%	55.78%	58.29%	**64.82%**	63.32%
	8 days	57.29%	55.78%	56.28%	60.30%	**63.32%**
	6 days	58.79%	54.77%	52.76%	61.81%	**68.34%**
	4 days	57.29%	55.78%	57.29%	54.27%	**59.80%**

IBM	10 days	60.30%	62.81%	61.31%	60.80%	**64.82%**
	8 days	59.80%	60.30%	59.80%	62.31%	**64.82%**
	6 days	55.28%	56.28%	59.30%	56.78%	**59.80%**
	4 days	46.73%	56.78%	54.27%	**57.79%**	52.76%
AMZN	10 days	64.80%	52.80%	61.20%	62.80%	**69.60%**
	8 days	61.60%	53.60%	60.00%	58.00%	**64.80%**
	6 days	61.20%	58.40%	59.60%	56.40%	**61.60%**
	4 days	**64.40%**	60.80%	64.00%	60.40%	61.60%
GOOG	10 days	55.28%	59.30%	53.77%	55.78%	**67.34%**
	8 days	57.29%	59.30%	56.28%	56.28%	**67.34%**
	6 days	56.78%	57.29%	57.29%	**58.79%**	**58.79%**
	4 days	54.27%	53.77%	56.78%	59.30%	**62.81%**

4.6. Improvement in Stock Trend Prediction based on the Joint Network

A collaborative network using multiple channels that can incorporate full features from sentiment analysis as well as a candlestick chart was proposed to enhance the stock prediction result. The different aspects of the collaborative network with the help of accuracy evaluation as well as accuracy level matrix evaluated on 5 of the main stocks. After this process the stock change prediction was evaluated by the proposed model for various periods.

The examination of how every component would affect the proposed method of the prediction performance has been discussed here and three models evaluated were the sentiment analysis model, candlestick model, full model, etc.

Sentiment: the sentiment analysis network depends on the data from social media as well as 1D convolution and neural network.

Candlestick chart: the 2D convolutional neural network depends on the candlestick chart data, one upon going through the below table will get to know about the different studies on different periods that are 4 days, 6 days, 8 days, and 10 days. To understand the highest accuracy and accuracy level, it has been highlighted in bold and it has been observed that the performance improvement has been achieved when the proposed method was utilized which indicates the advantages of stock prediction with the help of the multi-channel network. According to the below table, it can be predicted that the sentiment network has worked better when the 4 days were considered than the proposed method of periods which is 6 days, 8 days, and 10 days. When the candle chart data was used for the single-channel network, it helped in the enhancement of the accuracy performance by 8%.

Table 2: Accuracy improvement in stock trend prediction based on joint network

Stock	Time Period	Sentiment Accuracy (Accuracy_Level)	Candlestick Chart Accuracy (Accuracy_Level)	Joint Network Accuracy (Accuracy_Level)
AAPL	10 days	71.36%	62.81%	75.38%
	8 days	71.86%	61.31%	74.37%
	6 days	65.33%	57.29%	66.83%
	4 days	**67.84%**	61.31%	64.82%
TSLA	10 days	63.32%	50.75%	71.86%

	8 days	63.32%	52.76%	69.35%
	6 days	**68.34%**	56.28%	64.32%
	4 days	59.80%	52.76%	64.32%
IBM	10 days	64.82%	47.74%	**67.84%**
	8 days	64.82%	49.25%	**69.35%**
	6 days	59.80%	49.25%	**60.08%**
	4 days	**52.76%**	44.72%	51.26%
AMZN	10 days	69.60%	61.20%	**74.80%**
	8 days	**64.80%**	57.60%	64.00%
	6 days	61.60%	56.40%	**67.60%**
	4 days	61.60%	60.40%	**66.00%**
GOOG	10 days	**67.34%**	54.77%	**67.34%**
	8 days	67.34%	56.28%	**67.84%**
	6 days	58.79%	56.78%	**60.30%**
	4 days	**62.81%**	57.29%	62.31%

The uses of the accuracy level matrix seem to come out with the same conclusion and table which has highlighted the utilization of the multi-channel proposed network has shown a favourable outcome in comparison to the single sentiment network as well as the single candlestick chart network indicates about the stock traders who have a higher chance of profit booking when the proposed method was utilized.

4.7. Stock trend prediction in different periods

According to table 3 and figure 2, one can go through the performance of the five high-demand stocks (AAPL, TSLA, IBM, GOOG and AMZN) based on the proposed method for the various periods. The stocks are highlighted in bold with the highest accuracy, precision, recall, and F-score. Figure 2 highlights the prediction accuracy has enhanced gradually from Day 4-to 10 and it highlights that the performance of the stock over a long period has shown a better result in comparison to a shorter period. This is generally because of the movement trend of the stock over a longer period, and this contributes to the prediction accuracy over a long period. As shown in the above table, the proposed method was able to successfully achieve the most favourable performance on AAPL stock with 75.38% accuracy over a 10-day time. On the contrary, the least favourable performance was achieved in the IBM stock with 51.26% accuracy over a period of 4 days. Also, our model was able to achieve the most balanced results for TSLA stock with 79.59% recall, 71.86% accuracy, 73.58% F-score and 68.42% precision over a period of 10-days.

Table 3: Performance of proposed method for 5 high-demand stocks on different time periods

Stock	Time Period	Accuracy	Precision	Recall	F-Score
AAPL	10 days	**75.38%**	**68.66%**	**62.16%**	**65.25%**
	8 days	74.37%	76.00%	49.35%	59.84%
	6 days	66.83%	64.18%	50.59%	56.58%
	4 days	64.48%	65.22%	19.48%	30.00%
TSLA	10 days	**71.86%**	**68.42%**	**79.59%**	**73.58%**
	8 days	69.35%	70.37%	60.64%	65.14%
	6 days	64.32%	60.53%	52.87%	56.44%
	4 days	64.32%	60.75%	69.15%	64.68%
IBM	10 days	67.84%	**72.73%**	61.53%	66.67%
	8 days	**69.35%**	70.83%	**67.33%**	**69.04%**
	6 days	60.80%	65.33%	48.51%	55.68%
	4 days	51.26%	57.83%	43.64%	49.74%

AMZN	10 days	**74.80%**	68.09%	**65.98%**	**67.02%**
	8 days	64.00%	61.11%	41.51%	49.44%
	6 days	67.60%	**68.42%**	47.71%	56.22%
	4 days	66.00%	60.94%	39.39%	47.85%
GOOG	10 days	67.34%	**82.05%**	35.56%	49.61%
	8 days	**67.84%**	78.05%	**36.78%**	**50.00%**
	6 days	60.30%	57.78%	30.23%	39.69%
	4 days	62.31%	66.67%	23.53%	34.78%

Figure 4: Performance of proposed method for 5 high-demand stocks on different time

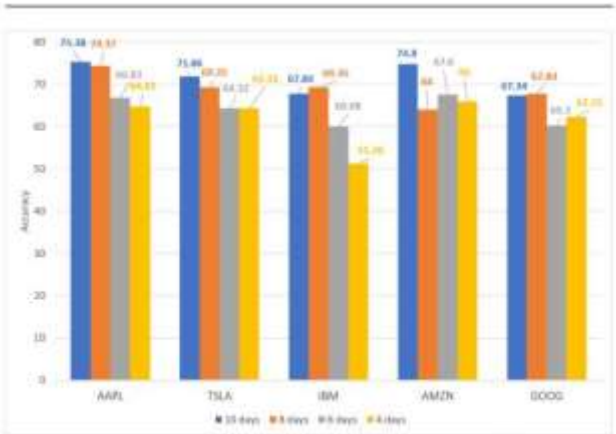


Figure 5: Prediction for 5 high-demand stocks on different time

5. Discussion

In this section, we discuss contributions, implications, limitations, and future research.

5.1. Contributions to the Literature

This research paper has developed a prediction model using sentiment analysis and CandleStick Charting for predicting the stock market prices. The results show that the investment strategy based on the proposed prediction model can help in generating significant returns as it has superior predictive power. Natural Language Toolkit was initially used for performing sentiment analysis on the textual tweets uploaded on Twitter. This toolkit helped to gain insights into the sentiments of the users about a specific stock. An overall sentiment score was obtained for a given day for the stock from the results of classifying sentiment analysis. Later, candlestick chart images were generated depending upon the historical time series data for visualizing daily stock movement and price for a specific stock. Computer graphics techniques were used for this method. Our proposed prediction model gives promising results for stock prediction and surpassed the performance of other networks that used either sentiment analysis alone or single candlestick charting. Hence, it proves that the use of both types of data tends to be more effective in predicting stock movement as the use of both types of data can significantly affect the price movement and decision of investors for a specific stock.

The research paper has highlighted how the candlestick bar comprises a wide bar and the vertical line where the bar is pierced vertically. Moreover, keeping aside the existing methods, the paper has not relied on the sentiment analysis of the social media post; rather, they did not focus on exploring patterns in the candlestick chart solely. A collaborative network has been proposed by the paper by implementing candlestick charts and the data from social media for predicting the stocks. As per the knowledge of the researcher, this has been the first study to apply both candlestick charts and social sentiment data for predicting the price of the stock. The utilization of both types of data has proved to be effective in predicting the trends of stock prices as the stock price movements and decisions of traders can be affected and changed through these two data types.

The examination of different representations of the text of news articles was done to determine the future stock price in comparison to linear regression with SVM with a prediction system called Arizona Financial Text (AZFinText)(Schumaker, et al., 2012). To get better accuracy, the implementation of other machine learning techniques for example Relevance Vector Regression is to be considered. To have daily full-length news article summarization that would help in the stock price prediction, the introduction of sentence-level summarization was done by (Nemes & Kissa, 2021). The paper has successfully analysed the generic stock price prediction framework considering the textual document as the inputs and quite predicted price movement as the output.

5.2. Limitations and Future Research

The paper has discussed the correlation between the Twitter sentiment as well as stock movement and data from the paper highlighted that only 3.5% of news and 8.5% pass along values makes the data of Twitter less convincing as compared to the 40% of the tweet (Xu, 2020). The paper found that there is a large amount of data on the Twitter platform and most of them are not relevant to the study and going through the data is just a waste of time. Hence, to stay away from wastage of time and resources, the stock market prediction can be done through StockTwits by replacing Twitter.

Although the prediction framework provided in this paper has predictive power, still certain stop-trading rules (for example, in the Chinese market) make it difficult to get profit from certain patterns. The SVM method is not considered to be suitable for the stock prediction of large-scale data. Hence, more suitable methods of machine learning like Reinforcement Learning Methods should be incorporated into the ensemble model. Also, the primary research has given rise to a few challenges and one of the major challenges is the dataset. The researchers have highlighted that the history of data is available publicly but the source for the text data is not accessible. Another challenge that has been faced by the researchers is to get the correlation between the sentiment analysis and technical analysis. The reason why they have faced challenges to explore the chemistry in between the two parameters is that there is very little work that is publicly available for the combination of these two analyses hence it will be of great interest to look whether these combinations would help in ensuring the accuracy of the prediction of stock movement. Lastly, there have been many published work-study of the Japanese candlestick charting, but the result of this research is very controversial. The research paper has discussed both sides of the study on Twitter sentiment. For future research, the focus needs to be made on the additional predictive factors like market sentiment and major news events that can also be utilized for improving the results of prediction.

5.2. Limitations and Future Research

Our machine learning model can be efficiently and effectively adopted into investment management practices. Thereby, investors and fund managers can generate new insights from data from non-traditional sources such

Facebook and Twitter social medial platforms, which are unstructured and often not analyzed efficiently and effectively. The research paper has highlighted that the investors have been benefited due to technology and they trade stocks way differently. Previously, the investors read outdated newspapers and used the telephone to order the stocks but now they are always updated with the latest news in real-time across the globe (Malkiel & Fama, 1970). All these things have to lead to a drastic change in the investment of the investors and they can make precise decisions by acquiring information about the stocks. The research paper has cited that the information has grown rapidly over the past few years in an exponential manner and social media is one such factor that has helped in growing the amount of information. Facebook and Twitter are the most important social media platforms from where people get a lot of information about the stock (Chen, et al., 2017). There is no doubt in the fact that social media popularity has captured the attention of many researchers in the field of social media sentiment. In September 2019, Volfefe Index was released by JP Morgan to showcase the stock market volatility for the treasury bonds of the US because of the influence of President Donald Trump's tweets (Volfefe index, 2019). When Donald Trump became the 45th President of the United States of America, his tweet has greatly impacted the stock market in 2016 and our approach is relevant to other application areas of management where twitter data can provide incremental but valuable drivers or impact on people's behaviours.

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