STOCK MARKET FORECASTING USING RECURRENT NEURAL NETWORKS AND LSTM

R.Lalitha
Professor
Department Of Computer Science and Engineering
Rajalakshmi Institute Of Technology
lalitha.r@ritchennai.edu.in

Harish Kumar.R
Department Of Computer Science and Engineering
Rajalakshmi Institute Of Technology
harishkumar.r.2019.cse@ritchennai.edu.in

Jayaraj.S
Department Of Computer Science and Engineering
Rajalakshmi Institute Of Technology
jayaraj.s.2019.cse@ritchennai.edu.in

Abstract -- A very exact prediction of a future trend is crucial in an economically unpredictable atmosphere like the stock market. Due to the economic recession and the demand for earnings, it is vital to have a solid stock market forecast. Stock investment methods are intricate and require large amounts of data research. Investors in stocks have persevered in their pursuit of the best of the two business traits, employing predicting machine learning systems to aid in their preparations. Yet, with numerous systems in use today, one may argue that the diversity of data on the basis of which they depend is insufficient. We investigated the usage of long-term short-term recurrent neural networks in stock forecasting and planned trials to improve the machine learning model's responsiveness in order to assure its effective adoption into our suggested predictive system. Our objective is to create a collaborative learning forecasting system that will make use of a variety of huge data resources.

Keywords: machine learning algorithm, stock market prediction, literature survey, artificial neural network, support vector machine, hybrid algorithm, long short term memory network

I.INTRODUCTION

Today, data is our only source of existence. Future stock market data prediction is a crucial financial topic that relies on the assumption that basic information that was made public in the past has some predictive ties to future profits on stocks. Forecasting the stock market involves a number of steps, including identifying market trends, making investment plans, figuring out when it's best to buy stocks, and selecting the right stocks. The stock exchange, also known as the investing business community, is a non-direct, non-para structure that is challenging to describe with any degree of accuracy. A certain stock must be purchased, sold, or held by this set of investors at a given moment in time. Analytical scientists are continually seeking methods to enhance current forecasting models, making prediction a fascinating area of inquiry. The objective is to provide businesses and individuals with investment opportunities so they may create a strong framework for their future ventures[20].

A number of these traders have produced some quite spectacular results as a result of applying machine learning techniques to the market lately due to the expanding relevance of machine learning across several industries.

With datasets comprising all past stock prices as well as data that will be utilized as training sets for the software, this study will develop a financial data prediction program. The basic objective of the forecast is to lessen the uncertainty around financial decisions.

Stock market forecasting has also been done using machine learning methods like ANN as well as support vector machines[5,22]. To find patterns and make predictions, these algorithms make use of sophisticated mathematical models and vast volumes of data[6,18]. Support vector machines and artificial neural networks, for instance, can be used to determine the most significant influences on stock prices[9] and to detect nonlinear correlations between the price of stocks and other variables.

Recently, scholars have begun to investigate the use of different information sources, such as news articles and social media, in stock market forecasting[21]. According to this research, using such data can contribute to the knowledge base and increase forecast precision. As an illustration, sentiment analysis may be used to assess the general tone of news stories and social networking posts about a certain firm, and this tone can then be used to forecast stock prices[4,16].

In recent years, ANN has become more often used in commercial settings. The market value of a share or index has been predicted using a great algorithm. The number of neural network research projects has significantly increased during the past ten years. Models of artificial neural networks are built on the neuronal architecture of the brain. Artificial neural networks and the brain both gain knowledge from experience. In order to analyze corporate data kept in computers or data warehouses, ANN is frequently utilized as a practical analytical tool. Two new areas of neural network study and application are identifying patterns in consumer behavior and stock price forecasting. Most companies have created new techniques for evaluating financial data and choosing investments. The majority of organizations employ Artificial Neural Networks (ANN) to enhance their analyses' predicting capabilities[11].

The primary goal of neural network prediction training is to identify an approximation of the mapping between data for input and data for output. Next, future values are predicted using the newly trained recurrent neural network. The use of an ANN approach to anticipate stock market values is discussed in this paper[1].

For predicting stock movements, several researchers frequently employ ANN techniques such as auto-regressive average moving average models, a couple of different kinds of backward propagation neural network models, and multi-layer perceiving [7]. Since a feed-forward neural network only takes into account the current input and has no memory of prior inputs, its main flaw is its incapacity to handle sequential data. For getting over this restriction, (RNN) is proving to be a popular choice. RNNs have also attracted a lot of attention lately in stock forecasting research since they are built to comprehend time-varying and linear patterns. LSTM is a form of RNN that appears to be capable of learning long-term dependencies.With the S&P 500 index, Gao et al.'s[7] technique for predicting closing stock prices showed that LSTM had a higher prediction performance than the previous 100/200/400 days. As previously indicated, LSTM has been used in various research [10,13,15,19] to predict stock prices. The specific characteristics of stock data make it impossible to predict with accuracy using traditional techniques like auto-regressive moving average (ARIMA), support vector regression (SVR), and random forest[8].

In this work, we outline and discuss research on forecasting approaches, as well as our suggested model for a system that uses large data to forecast stock prices, and how it can be enhanced further than is generally established using LSTM. Furthermore, we hypothesize that our structure will employ parallelization using the Ray framework [13] to reduce model training latency.

II. LITERATURE REVIEW

Stock return forecasting has recently been a popular topic of research. The research attempted to establish a linear relationship between macroeconomic conditions and stock returns in the majority of cases. Despite the appearance of variability in stock market return indices, various research in regressive statistical evaluation of stock return have appeared, with the bulk of them demanding that the regressive structure be specified prior to valuation. Nevertheless, since stock returns are generally chaotic, untrustworthy, inconsistent, and unexpected, RNN has been shown to be an approach that is more effective in collecting the structural link between a stock's performance with its deciding components than multiple different statistical analysis approaches. In the literature, many sorts of input factors are utilised to anticipate returns on stocks. In fact, multiple input parameters are used to anticipate the same collection of returns from stock data. Some research used a single time series as its information source, but others looked at the inclusion of additional market information as well as socioeconomic aspects. Some researchers went as far to actually prepare the data sets before submitting them to an RNN for prediction.

We retrieved and produced research articles and developed numerous ways for anticipating stock market circumstances and making it easier for investors to trade on the stock exchange. Among these techniques are:
(1) Artificial Neural Network (ANN),
(2) Support Vector Machine (SVM),
(3) ARIMA Model,
(4) Long Short-term Memory (LSTM), and
(5) Hybrid Methods.

The research in each category are analyzed to discover consistent findings, distinctive findings, constraints, and areas that need additional exploration. The final part summarises the general findings and potential research areas.

III.RELATED WORK

Anacostia Kowanda, Dionysia Kowanda, Muhammad Firdaus, Swelandiah Endah Pratiwi,[2]. This study reveals that the ability of ANN shows consistency of an accuracy rate of stock market prediction. Four method in predicting stock market had an accuracy above 95% The highest accuracy achieved by using Signal Processing/Gaussian Zero-Phase Filter (GZ-Filter) with 98.7% prediction accuracy.

Mahmoodi, Armin & Hashemi, Leila & Jasemi, Milad & Laliberte, Jeremy[12]. The purpose of this research is to use a suitable structure to predict stock exchange trading signals with high accuracy. To achieve this purpose, two methodologies for assessing technology adaptation are used. Suport Vector Machine (SVM) is used together with the method of particle swarm optimisation (PSO), when PSO is used as a quick and precise classification for examining the issue-solving space, as well as the results are then compared to the efficacy of a pair of further meta heuristic algorithms, including the neural network and the Cuckoo search algorithm (CS).

Bansal, Ankit[3].They indicated in this study that when the news mood for a particular stock is included, the results are probably going to turn out better. To forecast the future of market behaviour, the psychology of markets, behavioural economics, & statistical methods are employed. A reliable forecast for a stock's future value could prove incredibly useful. They often attempt to find the optimal combination of many forecasting models--LSTM, Prophet, and ARIMA--so that the prediction is as close to its original as possible. Using the implementation of technology, it will help in better assessing the marketplace for particular stocks and the error gap. It is largely focused with determining whether or not a current pattern is going to persist and, if so, when it's going to reverse.

Nadif, Mohammad & Samin, Md & Islam, Tohedul[14]. They offer an irregular technique centred on the Long Short-Term Memory (LSTM) structure. LSTM-based modelling outperform alternative approaches in forecasting time-varying and sequential models, based on studies, whereas RNN is an initial method with a memory inside that recalls its input, which makes it ideal for machine learning problems containing sequential data.

Rao, K. & Reddy, B. Venkata[17]. They present a successful approach improvement for forecasting the stock market using a hybrid machine learning (ML) model (HM-SMP) in this study. The initial addition of the proposed HM-SMP model involves the introduction of the chaos-enhanced firefly bowerbird optimisation (CEFBO) approach for optimal selection of features amongst multiple characteristics, thus lowering data complexity. Second, they develop a combination of multiple-purpose capuchin using a recurrent neural network (HC-RNN) for the stock market forecasting, which enhances the precision of predictions.

IV.METHODOLOGY FOR BUILDING THE MODEL

a. Gather previous stock information from a trustworthy source, such as Yahoo Finance or Alpha Vantage. To obtain such information, you may employ a Python tool such as pandas.

b. Adjust the data beforehand with a method like MinMaxScaler from the scikit-learn package. This will normalise the data from 0 to 1, allowing the LSTM algorithm to acquire the trends found within it more effectively.

c. Divide the data into two sets: training and testing. You can utilise a split ratio such as 80:20 or 70:30 for testing and training purposes.

d. Using Keras or TensorFlow, establish an LSTM model. Begin using a basic architecture consisting of several layers of LSTM and then add multiple dense layers for output. Dropout layers can be added to minimise excessive fitting.

e. Construct the LSTM model using data for training after which test it with testing data. To assess the efficacy of the model, utilise measures such as Mean Squared Error (MSE) or Root Mean Squared Error (RMSE).

f. Use a trustworthy news API, such as NewsAPI, to collect financial-related data. To get this information, you can utilise a Python library called requests.

g. Tokenize and encode the news data using a technology such as Word2Vec or GloVe. It will transform the written data into a number format that an RNN model can use.

h. Using Keras or TensorFlow, create an RNN model. Begin with a basic architecture consisting of one or two LSTM layers followed by a dense layer for output. Dropout layers can be added to reduce overfitting.

i. Develop the RNN model on financial data and then test it on a test data set. Metrics like accuracy and F1 score can be used to assess the model's performance.

j. Integrate the LSTM and RNN models to create a single model that can process both stock and news data. To merge the outputs of the LSTM and RNN models, use a concatenation layer, followed by an opaque layer for output.

k. Train the entire model on training data and then test it on testing data. To evaluate the model's performance, utilise measures such as MSE or RMSE.

l. Use a web framework like Flask to deploy the model as a web application. You may design a user interface that is interactive that allows users to enter stock symbols and view stock price forecasts using a frontend framework.

V.PROPOSED SYSTEM

The actual implementation of LSTM RNNs is available in a Python test module that we developed. At this point, these test modules are intended to perform the core objective of forecasting stock prices using data from time series. The test modules are designed to be comparatively modular in order to be modified to cope with the fresh input and then be tooled well with proper application to be used for the other implementations of LSTM RNNs afterward on. Regardless, they are currently designed to accept time series information in the format of CSV text files, one for training and one for testing. The test module generates several graphs as output.The test interact to produce several graphs that show the stock's historical price trend, rolling mean analyses of the price movements, and at last a chart that shows a comparative graph between both the true stock price and the anticipated stock price. In addition to these graphs, an accuracy value is available for the ultimate graph to provide a non-visual and cement basis for forecasting success. There is also some additional arithmetical information provided, such as time elapse values for monitoring the overall effectiveness of the test module. Presently, several libraries are utilized by our test modules to conduct their core objective of stock market prediction. These libraries and their implementations in our tool to monitor are as follows:

- Panda To create training sets to be utilised in the LSTM RNNsmodels' training, Panda is used to organise the incoming CSV data into data frames.
- Scikit-learn The MinMaxScaler function, which is used for data scaling, was provided by Scikit-learn.
- NumPy The time series datasets are formatted using NumPy into usable arrays and matrices.
- Datetime Based on the historical data information of the items in the datasets, datetime is utilised to arrange and format the input CSV data.
- Keras The procedures and tools needed to create and run LSTM RNNss are part of Keras.
- Matplotlib The test modules' various output graphs are plotted using Matplotlib, which is used to format data into a plottable form.
- YFinance One of the well-known Python modules for gathering web data is called YFinance, and with it, we may get Yahoo's financial information.
- TensorFlow Google created the open-source library TensorFlow specifically for deep learning applications. Traditional machine learning is also supported..
- Flask Python is used to create web applications with Flask, which is developed on Werkzeug and Jinja2. There are benefits to adopting the Flask framework. A quick debugger is offered, and there is an integrated development server.
- TextBlob is a Python package for text processing. It provides a basic API for popular NLP operations such as sentiment analysis, part-of-speech tagging, and noun phrase extraction.
- Requests is a Python package that allows you to make HTTP requests. In this code, it is utilised to retrieve financial news data from newsapi.org.
- Beautiful Soup 4 (bs4) is a Python web scraping package. The requests library is used in this code to fetch news items' HTML pages and extract data from them.

Those are the libraries that comprise and aid in the operation of the pre-parallelization test section. We had searched at several alternatives for parallelizing the test systems in the hopes of identifying the most effective way to accomplish so. We determined that the best way to accomplish this would be to use Ray, a Python library that is under development at the moment. The Ray library would allow the test component to be run on a single device in a decentralized way which wouldn't affect the test module's existing code. The Ray library includes a decentralized network framework that supports actor-based and task-parallel programming concepts. The actor-based fraction of the structure is the one we have at hand that want to concentrate on. Ray's actors enable the template to help facilitate the operation of stateful computations, such as model training in our case. Ray's cluster computing template is overall, which means that, in addition to our application, it can support a wide range of other applications such as visualising and affirmation learning. Actors in the Ray framework are domain specific estimators that, while implemented serially, we will try to use in parallelizing the processes that enable us to train our frameworks within in the test modules. If this does not result in a reduction in training latency, a task-parallel method can be utilized. This would entail designating functions as virtual tasks in order to execute them concurrently.Nevertheless, because epoch training is traditional sequential, this has the potential to cause issues with accuracy and general interventional safety of the training. Our solely issue is the potential effect on the accuracy of the forecasting analytics caused by implementing the epochs under this manner. Our predictive model is developed and executed almost entirely within the Keras library. As a result, the practical application of the Ray library could arise within the test section and must instead actually occur within the Keras library. Parallelization is possible with the Ray library execution within Keras, specifically as it resolves to the features that function the model building epochs.The previously stated possible effect on accuracy will be discussed and viewed when operating the test modules, which will then be contrasted to the pre-parallelization components to determine if any impact arises. We additionally have a technique to enhance the activity of the LSTM RNNs models by willing to host them in a virtual environment. We could easily control the resources needed to effectively test to determine if the parallelization of the test modules was effective or not in an enhanced performance test in this environment. This environment might also serve as a testing ground for our later proposed ensemble forecasting system.

Figure 1 shows a comprehensive overview of the systems architecture to provide our proposed prediction system greater perspective. The recommended system would accommodate a range of input datasets, like contractual data. Every single one of these data kinds will be turned into useful data for the LSTM RNNs modules. Each type of data will necessitate a distinct processing strategy, which may include word embeddings in NLP for economic news or basic data formatting for data from time series. Following formatting, the data may be utilised with LSTM RNNs modules to predict the result of whichever stock-related information we are interested in. Next, using an ensemble teaching approaches, each forecast will be used and allocated an alternative weighting. It is important to remember that the LSTM RNNs modules will now be distributed throughout the Ray cluster architecture inside the proposed design due to the possibility for improved efficiency. Although the precise weighting will be determined later, the general idea is that some financial data sources should logically have better correlations with the actual stock price and, as a result, receive more weight when generating the final projection. These outcomes from each module will be pooled and calculated within the ensemble learning system to provide a final output after being trained and processed on the cluster computing framework. At this moment, it is only speculative to speculate on the outcome. The theorised notion for what it may be is either a more weighted projection of what the price may be than the current estimate provided by the module. The outcome, however, can only be a return that indicates whether it is predicted that the stock price will rise or fall in relation to the day before to the intended date of projection. This potential architecture is currently rather high-level in abstraction and speculative, as the majority of its requirements have not yet been thoroughly studied. To fully realise these criteria, works like this one will run as effectively as feasible.

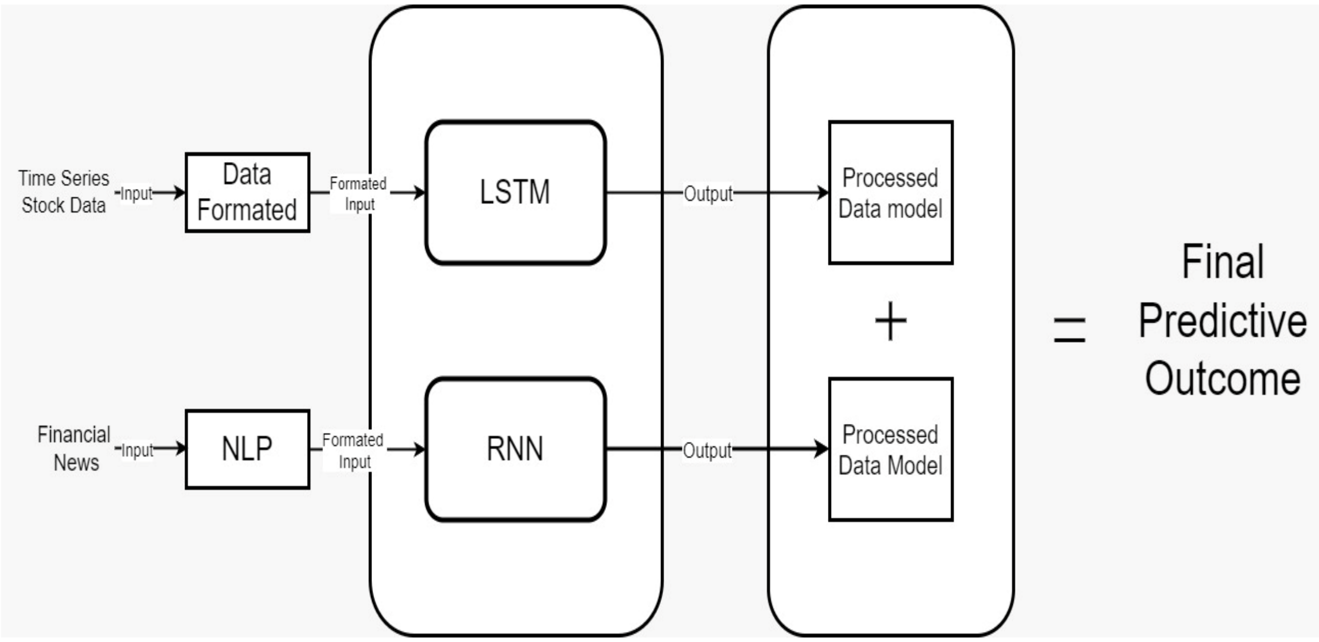

Fig. 1. Hypothesized predictive system utilizing ensemble learning architecture

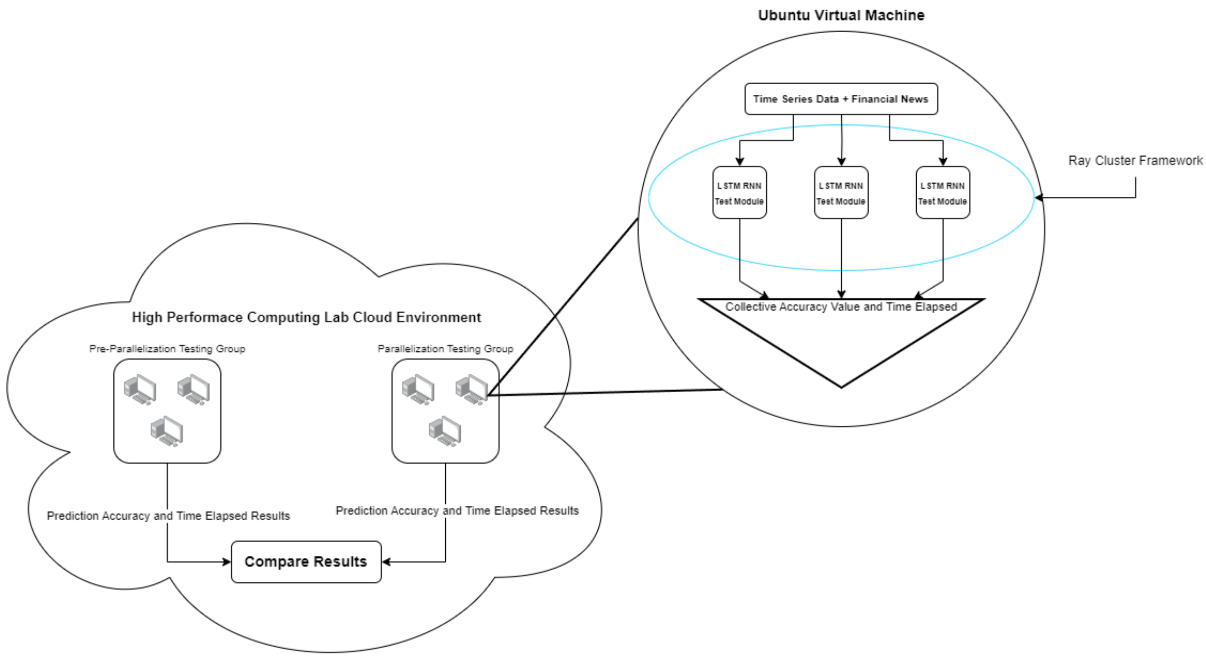

Fig.2.Illustrated Example of the Proposed Experiment Design

VI.RESULTS

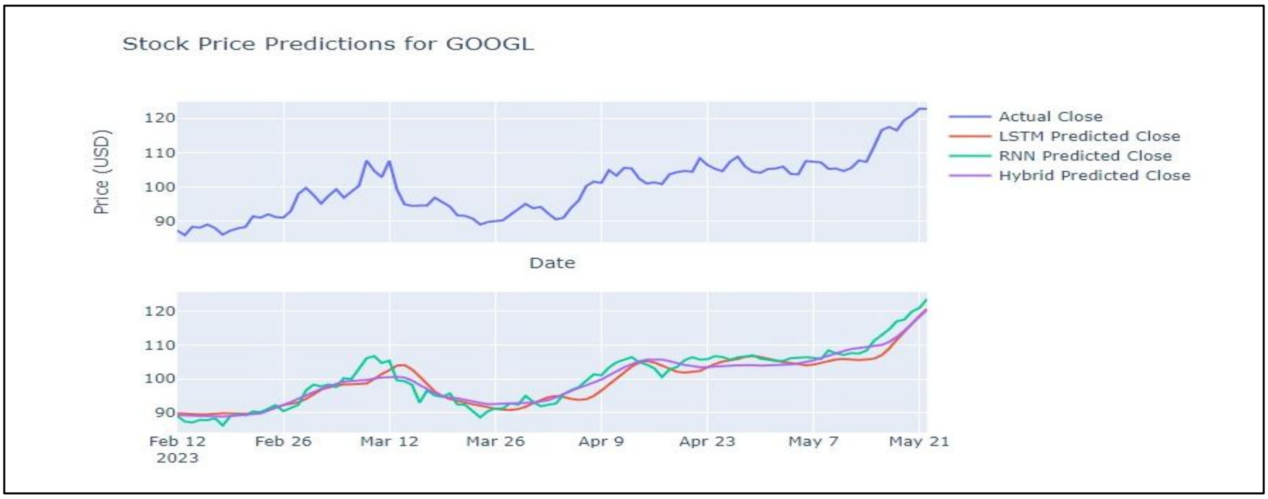

Fig 3.1

Fig 3.2

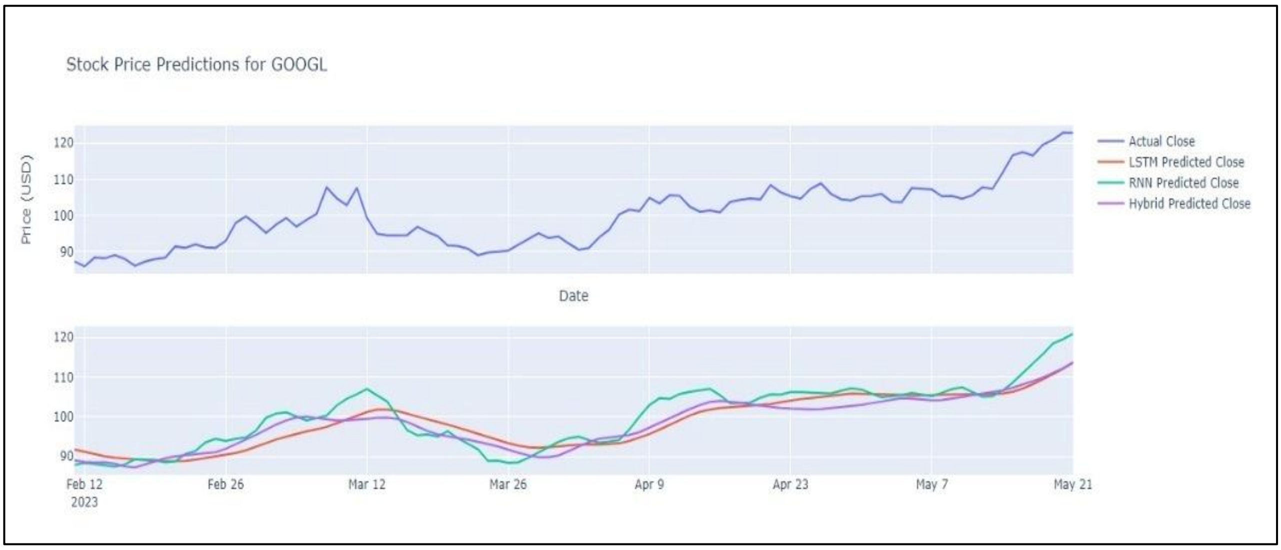

Fig3.3

Fig 3.1, 3.2 &3.3- Stock Prediction Graph

In Fig 3.1, 3.2 & 3.3 shows the prediction graph using recurrent neural network and LSTM. The data is of Apple Inc .Whereas in fig 3.1 10 years of data has been used and in fig 3.2 and 3.3 5 years of data and 1 year data has been used respectively. The data has been accessed from yahoo server.

VII.CONCLUSION

Finally, this work investigated the usage of LSTM and RNN algorithms on forecasting the stock market. The findings show that these types of models may provide reliable stock market forecasts and beat classic time series techniques including ARIMA, SVR, and random forest. The LSTM approach, in specific, outperformed other models in forecasting stock values over more extended periods.

The results of the research have practical consequences for clients and finance professionals who may use such models to help them make investment decisions. These predictive models can give extra insights into market patterns and assist discover prospective investment possibilities by combining additional sources of information including news articles and social media sentiment analytics.

Nevertheless, it is vital to recognise that forecasting the stock market can be a complicated and continuous process, with several factors influencing the value of stocks. Although the algorithms utilised in this study produced encouraging results, it is critical to continue investigating new techniques and methods for predicting stock markets. Future research might also concentrate on merging several statistical models and information sources to increase forecast accuracy and resilience. In general, this study emphasises the possibility of deep learning algorithms for predicting stock markets and lays the groundwork for additional research and development within this field of study.

VIII.FUTURE SCOPE

Neural networks frequently produce substantial findings; for example, in the prediction of weather, a rule of climate shift is less likely than a consistent climate pattern. This holds true for the stock market as well. The ability to combine data provided in many forms is critical to good forecasting. Because of the dispersed nature of knowledge processing, neural networks can accept a significant quantity of incorrect and insufficient input data. The strength of neural networks lies in their capacity to forecast effectively even in scenarios with ambiguous data, as well as in their potential pairings with other approaches. Regardless of the numerous advantages of artificial neural networks, there are a few constraints that will be addressed below. Certain approaches are carried out with inadequate reliability tests, data design, and lack of ability to determine the most effective topology for a particular issue field. There does not exist a proven method for creating an ideal neural network, rather the most effective network depends heavily on data supply and use.

Several of the constraints are as follows:
1. NN requires a big amount of prior data.
2. The optimum NN architecture topology remains a mystery.
3. For complicated networks, the outcome and accuracy may suffer.
4. The outcome must be statistically relevant.
5. More rigorous data design and analysis are required.

Other limitations concerning NN evaluation and implementation should be discussed in order to improve NN applications. Companies do and implement a large amount of research that is not published in scholarly indices.

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