Stock Market Prediction using Non-Linear Models

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***Abstract*—In the era of artificial intelligence, various intelligent optimization algorithms are constantly applied to predict the stock market. The purpose of stock market analysis, or stock price forecasting, is to forecast the profitability of the company based on current and historical data. Forecasting can be defined as predicting a future event or events by analyzing historical data. It covers many fields such as business and industry, economics, environmental science and finance. Nonlinear time series are created with nonlinear dynamic equations. They have properties that cannot be modeled by linear processes. This is where neural networks come in and we learn about RNN and LSTM methods.**

***Index Terms*—Time series data, forecasting, non-linearity, stock market, neural networks, RNN, LSTM, RMSE, R-Squared, MinMax Scaling, Normalisation, sliding window**

I. Introduction

The financial stock market is highly complex, nonlinear and uncertain, which makes it difficult to predict price fluctuation. It is one of the most volatile industries. Inconceivable growth if the prediction is accurate and an equally outlandish fall if it is not. With the advent of the era of artificial intelligence, a variety of intelligent optimization algorithms are constantly applied to the prediction of the stock market. Stock market analysis or stock price prediction is aimed at predicting firm's profitability based on current as well as historical data. From recent studies it is observed that machine learning approaches have outperformed traditional statistical methods in predictive analysis task. There are several shares available on the market. As a result, information on the shares and their linkages should have been available. With a proper grasp of stock prices, share prices, investment, audits, business portfolios, and so on, one may make sound decisions about where and how much to invest and identify and discover any misbehaviour. In instance, forecasting the behaviour of a finance stock only on the basis of its prior daily closing is also not a simple operation to undertake. To make educated selections regarding investing in the stock market, one must combine knowledge with dependable advice. Forecasting means prediction and is a technique that predicts the future value of selected data by looking at specific trends. It can be defined as the prediction of some future event or events by analyzing the historical data. It spans many areas including business and industry, economics, environmental science and finance. Time series adds a time order dependence between observations. This dependence is both a constraint and a structure that provides a source of additional information. While forecasting time series values, 3 important terms need to be taken care of and the main task of time series forecasting is to forecast these three terms. Seasonality is a simple term that means while predicting a time series data there are some months in a particular domain where the output value is at a peak as compared to other months. Stationary time-series data is a time-series data set that does not exhibit a trend or a seasonal effect. The random error is the only source of variability in the data set. Non-stationary time-series data is a time-series data set that exhibits a trend or a seasonal effect. The random error is no longer the only source of variability in the data set. For example, travel data when plotted shows a high peak towards the end of the year as we approach holiday season. The trend is also one of the important factors which describe that there is certainly increasing or decreasing trend time series, which actually means the value of organization or sales over a period of time and seasonality is increasing or decreasing. Unexpected events mean some dynamic changes occur in an organization, or in the market which cannot be captured. Common Time series models include ARIMA, smooth-based, and moving average. Not all models will yield the same results for the same dataset, so it's critical to determine which one works best based on the individual time series. To narrow down the specifics of your predictive modelling problem, we need to know about the volume of data we are dealing with more data is often more helpful, offering greater opportunity for exploratory data analysis, model testing and tuning, and model fidelity. Required time horizon of predictions- Short, medium or long term?Shorter time horizons are often easier to predict with higher confidence. Forecast temporal frequency- Often forecasts can be made at a lower or higher frequency, allowing you to harness down-sampling, and up-sampling of data, which in turn can offer benefits while modelling. Forecast update frequency- Updating forecasts as new information becomes available often results in more accurate predictions. While time series analysis is all about understanding the dataset; forecasting is all about predicting it. Time series analysis comprises methods for analysing time series data in order to extract meaningful statistics and other characteristics of the data. Time series forecasting is the use of a model to predict future values based on previously observed values. We have applied time series forecasting to our non-linear data set. Which brings us to the topic of non-linearity. Nonlinear time series are generated by nonlinear dynamic equations. They display features that cannot be modelled by linear processes: time-changing variance, asymmetric cycles, higher-moment structures, thresholds and breaks. Linear data is data that can be represented on a line graph. This means that there is a clear relationship between the variables and that the graph will be a straight line. Non-linear data, on the other hand, cannot be represented on a line graph. This is because there is no clear relationship between the variables and the graph will be curved. While linear data is relatively easy to predict and model, non-linear data can be more difficult to work with. However, non-linear data can also provide more insight into complex systems. A linear equation is always a polynomial of degree 1, whereas higher degree polynomials are nonlinear. We show that financial markets are usefully described as open physical systems. the autocorrelation function of volatility increments yields a value of about -0.4 at one-day time lag that is nearly equal for all stocks we analyze. Conditioning the evaluation of the autocorrelation function, we show that the market response is non-linear and strongly stabilizing when external shocks push for higher volatility. Autoregressive (AR) models are defined as regression models in which the dependent or response variable is a linear function of past values of the dependent/response variable. The order of an autoregressive model is denoted as 'p', which represents the number of lags used to predict the current value.A moving average (MA) is a type of model used for time-series forecasting. The moving average models are primarily used for stationary data, the data where we don't see significant trends or seasonality. The autoregressive moving average (ARMA) model is a combination of the autoregressive and moving average models. The ARMA model is defined as a regression model in which the dependent/response variable is a linear function of past values of both the dependent/response variable and the error term. The autoregressive integrated moving average (ARIMA) model is a generalization of the ARMA model. The ARIMA model is defined as a regression model in which the dependent/response variable is a linear function of past values of both the dependent/response variable and the error term, where the error term has been differentiated 'd' times.SARIMA is a type of time-series forecasting model that considers both seasonality and autocorrelation. SARIMA models are based on a combination of differencing, autoregression, and moving average processes.Data normalization is generally considered the development of clean data. With normalization, an organization can make the most of its data as well as invest in data gathering at a greater, more efficient level. Normalization is useful when your data has varying scales and the algorithm you are using does not make assumptions about the distribution of your data, such as k-nearest neighbors and artificial neural networks. One of the primary objectives of normalization is to bring the data close to zero. That makes the optimization problem more "numerically stable".One such algorithm for normalisation is min max scaler. MinMaxScaler may be used when the upper and lower boundaries are well known from domain knowledge. In this technique of knowledge normalization, a linear transformation is performed on the first data. Minimum and maximum value from data is fetched and each value is replaced according to the following formula: (x-xmin)/(xmax-xmin). Other methods for normalisation are: Feature clipping, which is used If your data set contains extreme outliers, this method caps all feature values above (or below) a certain value to fixed value. Log scaling computes the log of your values to compress a wide range to a narrow range. Log scaling is helpful when a handful of your values have many points, while most other values have few points. Z-score is a variation of scaling that represents the number of standard deviations away from the mean. You would use z-score to ensure your feature distributions have mean = 0 and std = 1. We have used the minmaxScaler as we have also applied the sliding window technique. We have set the window size to 100 on both the train as well as test dataset, and hence the MinMaxScaling algorithm works the best along with this to provide maximum accuracy. The use of prior time steps to predict the next time step is called the sliding window method. For short, it may be called the window method in some literature. In statistics and time series analysis, this is called a lag or lag method. The number of previous time steps is called the window width or size of the lag. The size of the window and segment increases until we reached the less error approximation. After selecting the first segment, the next segment is selected from the end of the first segment. The process is repeated until the whole time series data is segmented. In our dataset, this is set to 100. This value of 100 has been found via the hit and trial method, as we had initially started with values like 10,20 etc., and scaled up to 100 which provided us with the level of accuracy we need. Now coming to the we have methodologies applied on this non-linear model. Neural Networks are set of algorithms which closely resemble the human brain and are designed to recognize patterns. They interpret sensory data through a machine perception, labelling or clustering raw input.Recurrent Neural Network is a generalization of feed-forward neural network that has an internal memory. So how does this work? RNN is recurrent in nature as it performs the same function for every input of data while the output of the current input depends on the past one computation. Because of their internal memory, RNNs can remember important things about the input they received, which allows them to be very precise in predicting what's coming next. It can model sequence of data so that each sample can be assumed to be dependent on previous ones. Long Short-Term Memory (LSTM) networks are a modified version of recurrent neural networks, which makes it easier to remember past data in memory. In LSTM, 3 gates are present, input gate, forget gate and output gate. They deal with vanishing and exploding gradient problem. The gates allow for a better control over the gradient flow and enable better preservation of long-range dependencies. In order to test out our model, algorithm and the methodologies applied, we check the rmse and r-squared vales. Root mean square error or root mean square deviation is one of the most commonly used measures for evaluating the quality of predictions. It shows how far predictions fall from measured true values using Euclidean distance. R-squared is a statistical measure that represents the goodness of fit of a regression model. The ideal value for r-square is 1. We have obtained a value of 0.99. Finally we get to the implementation. We implemented our code in Python. We also saw the importance of a transformation function that helps change the dimension of data. For example, minmax scaling requires 2D input and we used a transform to convert a vector to 2d. Also, LSTM takes 3D input, so it's used there too. We have also used various functions like model.add for multiple layers which is useful for handling complex inputs, model.fit for training etc. We will see the correct application of these methodologies in the following chapters.

II. Literature Survey

We have reviewed related activities in the technical and financial fields, respectively. Using a customised deep learning algorithm and multiple feature engineering, Jingyi and M. Omair [1] forecasted data. The authors gathered data over a two-year period from the technical and financial stock market analysis research communities in China. Additionally, MLP, PCA, and feature selection were used. The artificial neural network-based solution for the Brazilian stock market was presented by Suellen and Mariana [2]. Using 5 different neural network designs, Jingyi and M. Omair are comparing predictions. IKN-ConvLSTM, a hybrid structure based on DNN, CNN, and LSTM that Isaac and Adebayo [3] proposed, is a multi-pronged stock analysis. They specifically created a framework to include stock-related data gathered from various sources. Predicting and analysing financial data takes a lot of time, ac- cording to Pengfei and Xuesong [4], and it is an issue that is time-dependent. The price chain employed the space-cycle sequence model (PSR) to reconstruct the pricing data for financial products as an all-encompassing complicated multi-time hypothetical sequence. Here, the findings show that the suggested prediction model can predict data with a high degree of accu- racy. A DNN-based network model for LSTM is integrated with the PSR approach for time series analysis. They used the SP 500 data set for their research.This work by Kang and Guoqiang [5] looked at ways to get rid of the most significant and impactful stock market items while making the most of the LSTM, SVR, ANN, and GAN usage models. SP 500 daily stock data was chosen by the author for a variety of trading information. Nayyeri and Nabipour [6] Data gathered for the organisation, based on 10 years of historical records, is used in this work. Use a variety of cutting-edge machine learning techniques to anticipate future value prices. This study made use of the emerging Iranian ten-year stock data set from 2009 to 2019. Neufeldb and Pushpendu [7] The authors of this article used an LSTM network and a random forest. SP 500 data was gathered by the author for intraday trading from January 1993 to December 2018. Daily returns for closure rates have matching daily returns for LSTM and informal forests of 0.41 percent and 0.39 percent, respectively. The first five steps of the procedure are compared in this research, including step two, which separates immature data during study sessions and divides each study period into training (in-sample trading) and trading (non-sample forecasts). The third stage of the target set, known as the featured features, is where the two machine learning techniques, random forest and DNN LSTM, are employed to partition the setting. The fifth and final step was developing a trading strategy for the trading section. Achyut and Soumik [8] looked at the development of businesses in many industries to determine the ideal time period for forecasting share prices in the future. They compared the outcomes using the LSTM model utilising the data sets from HDFC, ICICI, and SBI. Applying financial time series data, specifically the SP 500 stock index, Carl and Oscar [9] assessed the effect of various time steps on an LSTM model. However, Hyejung and Kyung's [9] temporal characteristic of stock market data is investigated in this study, which proposed a systematic technique for figuring out the size of the timing window and the topology of the LSTM network using GA. The results show that changing the time steps on this specific LSTM model has no effect on the model's predictive power. They also suggested developing an RNN-based stock price model utilising LSTM units, one of the most popular techniques for in-depth learning. Ankit and Kinjal [10] extended their examination of other precisely focused financial prediction issues and gave a thorough assessment of the merger data on the stock market projection. The writers drew conclusions on the value of employing fusion in the stock market and offered potential future indicators based on the literature they had studied. By examining articles that utilised the mixing strategies of various stock market applications, they developed a systematic approach to presenting the research for the years 2011–2020 and distinguished them- selves broadly in information integration, feature integration, and model integration.Indicator forecasting, portfolio management, risk analysis and return forecasting, pricing and trend estimations, and other stock market applications are just a few. Hiransha and Gopalakrishnan [11] employed the Multilayer Per- ceptron, Recurrent Neural Networks, LSTM, and CNN deep learning models to estimate the company's stock price based on historical prices that were accessible. The National Stock Exchange (NSE) of India and the New York Stock Exchange's closing prices of trading were utilised (NYSE). In order to anticipate the stock price of INFRATEL, one of the most competitive firms in the world, the author employed an in-depth learn- ing model and a neural network (ANN), according to a process given by Padmaja and Anandan[12].Bijit and Sreyash [13] The dataset for Amazon stock prices from 2010 to 2020 was used to test the LSTM prediction module. Both time series and sequential data are suitable for LSTM, which employs a multivariate method. The author compares sentiment analysis and expected stock value to show how closely the two are related and how people's attitudes affect stock prices in the future. The author also compares prediction with and without sentiment analysis data. Long-Short-Term Memory (LSTM) was created by Moghar and Adil [14] and RNN has a higher prediction accuracy. The author of this paper used data from Google and Nike open prices. [15] The experimental part of this study mainly covers the selection of the stock dataset of financial markets and the pre-processing and selection of the network results, followed by the description of the forecasting steps of the regression model FSVM. The results were analyzed by parameter selection, comparison of the accuracy of regression models with different optimization algorithms, analysis of prediction results and analysis of prediction effect errors. The conclusion is that the Fuzzy Support Vector Machine algorithm used in this study significantly improves the accuracy of stock market forecasting. First is the problem with asynchronous transaction intervals. Since the time interval of stock market transactions is random, the observation time interval is not the same but random. The problem is whether to record data according to each event or to record data according to a specific interval. Second, periodic data on stock markets have regular patterns throughout the day. Compared to low frequency data, high-frequency data has a strong periodicity, so we ignore the periodic effect during processing, which leads to a wrong conclusion. High-frequency research indicators include: volatility, bid-ask spreads, high-frequency event data, etc. We need prior information to select the model, we can use exhaustive methods, cross-validation methods, grid search method, intelligent optimization algorithm, etc. In the training sample set of fuzzy support vector machine, the proportion of each sample in the classification is different. Different degrees of membership are determined according to the different contribution of the sampling points in the classification to reduce the negative effect of outliers and noise on the classification surface. Fuzzy Support Vector Algorithm Classification Steps: Initial Data Acquisition, Sample Membership Calculation, Fuzzy Image, Kernel Functions and Parameter Optimization, fsvm Model Training, Testing. Prediction process - data processing, network structure layout, FSVM model prediction. As you can see from the following two graphs, the prediction results of individual stock prices using SVR are relatively perfect. In this way, the required attribute values can be predicted, as long as the other attribute values of the day are known with a fixed price value, according to which most investors can weigh the dynamics of the stock market. This study proposes a method for parameter selection and uses other stock prices to test its effectiveness. It can also be seen from the test results that the fuzzy regression support vector machine has a higher accuracy in stock price prediction, which is better than the time series model. The proposed approach takes a sample of X in the form (Xik ...,Xi2,Xi1,Xi) whose input is X and which contains price information and also has technical indicators as described. the above was used to predict yj. Many factors could be used to predict inventory, but many of them had constant values over time. Therefore, they were ignored in the raw data analysis. First, the dataset must be cleaned using outlier analysis and normalization techniques. Now the processed data set is used as input data. 5. Proposed model architecture. [16] For SVM, which extracts its most produced features, and these features are fed into an LSTM model and further trains an LSTM classifier, creating a predictor to estimate and return whether the stock price will rise or fall in the next week. The LSTM model must be tuned for different parameters, such as changing the number of LSTM layers, increasing the drop value or increasing the number of epochs. To improve the predictive power, the author has provided some detailed observations in the following sections. With a convolutional neural network, the process includes data preprocessing, data standardization, implementation and processing of trend indicators, etc. [17] The forecast model input contains two parts: basic event data and technical indicator data. A total of two experiments are proposed in this section. The first experiment examines the performance differences between CNN-M and Resnet-M; The second experiment examines the effect of network layers on CNN-M and ResnetM. Using deep learning and FLASK testing, we used "adam" as our optimizer. We also tested other optimizers, but "adam" performed better than other optimizers. We also added stopping layers to the neural network models to reduce overfitting. RNN stock values are created as a data structure such that each value is predicted based on the previous 60 stock values. Using a stacked LSTM Next, the same data set was trained using a multilayer LSTM. The MSE for this experiment is 0.0029. The number of epochs is 30. Applying two-way LSTM. [18] To forecast oil stock prices for, Indian government stakeholders using hyperparametric LSTM models, we collect historical stock prices for a ten-year period from 01/01/2012 to 12/31/2021. These numbers indicate the duration. To provide test data for model-based forecasts, we collect historical stock prices monthly from January 1, 2022 to January 31, 2022. January consists of the beginning and end of the month. Prophet's algorithm first identifies groups of similar products using brand and category information. Within each group, ensure that products are consistent within the historical range and obtain serial data for total sales. We then have to divide the whole period (usually a year) into the correct sub-periods. Let k be a certain distribution method, for each Xn the average sales of each subperiod are calculated and a series of average sales is obtained. A basic seasonal factor is then calculated, which is defined as the average of the seasonal factors calculated across similar product groups. [19] Finally, normalize the main factor in the time window. , FS- Prophet consists of three modules: S-Prophet for products with sufficient historical data, FProphet for products lacking full-cycle historical data, and a sales decline model to adjust forecast values during periods of sales decline. Compared to the basic Prophet model, which is commonly used for seasonal sales forecasting, our framework shows an overall improvement of 20.79percent. Analysis of financial market trends based on autoregressive conditional heteroskedastic model and BP neural network forecasting. [20] Researchers have extended the univariate GARCH model to multivariate ones, which can capture the dynamic relationship between multiple asset-return variation processes. The advantage of the GARCH model is that the positive certainty of the covariance matrix is guaranteed under very weak conditions and fewer parameters are needed to be estimated. [21] The number of nodes in the hidden layer determines the training accuracy of the network. If the number is too small, the weight of the network is not enough and a good predictive mathematical model cannot be obtained. If there are too many numbers, the network structure may be too complicated, so the convergence of the network is not good and may lead to over configuration. Generally, an empirical formula is used to obtain the area value, followed by trial and error. In the formula, h represents the number of nodes in the hidden layer, p represents the number of nodes in the input layer, q represents the number of nodes in the output layer, which is 1, and refers to the financial market model-based standard component analysis.

III. Proposed Methodology

RNN and LSTM are two of the three deep learning architectures we employed for this project. In a type of neural network known as an RNN, the connections between the computational units are arranged in a directed circle. RNNs, as opposed to feed-forward networks, can process inputs in any order using internal memory. An RNN's computational units each have changeable weights and real-valued activations that change over time. Recursively applying the same set of weights over a graph-like structure yields RNNs. The values of their hidden units are defined by many RNNs. Designing sliding panes allows for viewing the data usage sequence. The system's architecture will be impacted by the design of the sliding windows. The input and output models of the employed LSTM RNN will be determined by the design model.

The models used in our code are:-

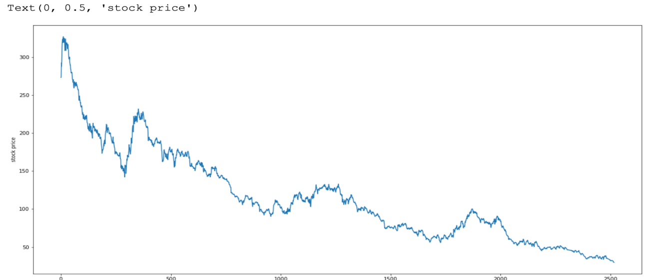
1) Sequential
2) Dense
3) Stacked

The dataset contains Apple AAPL Historical Stock Dataset from 2010-2020. The attributes we used are Date, Last/Close, Volume,Open, High, Low. While applying LSTM model, it is very important to normalize the dataset. Hence we have used MinMax scaler to normalize our dataset.

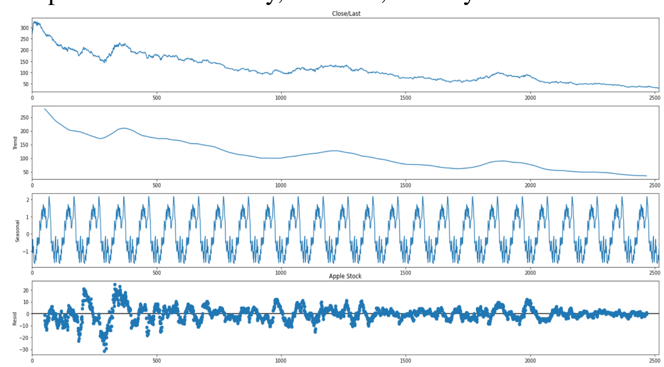
Results

We plot the data using close/last attribute as our y value and date as x-value.

```
Text(0, 0.5, 'stock price')
```



We again plot the dataset but now using trend, seasonality and residual as factors. The trend component of a time series represents a persistent, long-term change in the mean of the series. The trend is the slowest-moving part of a series, the part representing the largest time scale of importance. In a time series of product sales, an increasing trend might be the effect of a market expansion as more people become aware of the product year by year.We say that a time series exhibits seasonality whenever there is a regular, periodic change in the mean of the series. Seasonal changes generally follow the clock and calendar – repetitions over a day, a week, or a year are common.



We have attached the results of our predicted value and test data values.

```
In [24]:
y_pred = scaler.inverse_transform(model.predict(X_test))

In [25]:
y_test = scaler.inverse_transform(y_test.reshape(-1, 1))

In [26]:
y_pred[:5]
Out[26]:
array([[93.37183 ],
       [94.230965],
       [94.368225],
       [94.34008 ],
       [94.78538 ]], dtype=float32)

In [27]:
y_test[:5]
Out[27]:
array([[94.4728],
       [94.1985],
       [95.3007],
       [97.3314],
       [95.0257]])
```

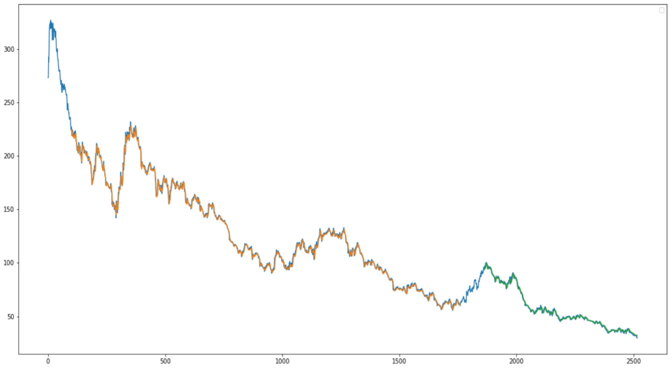
A. Evaluation

We have used RMSE and R-squared to measure the accuracy of our model.

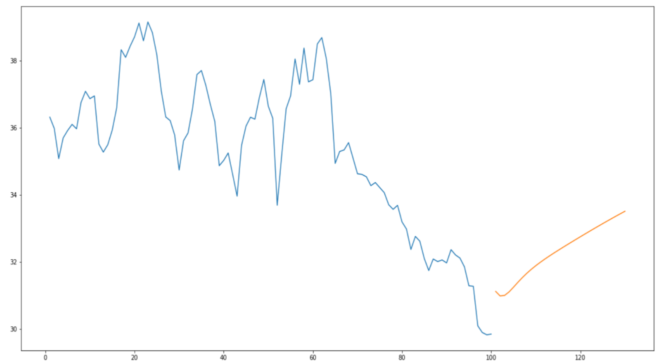
evaluation

```
In [28]:
import math
from sklearn.metrics import mean_squared_error

rmse_score = math.sqrt(mean_squared_error(y_test,y_pred))
print('Root Mean Squared Error(test) : ',rmse_score)

Root Mean Squared Error(test) :  1.4853871963289433

In [29]:
from sklearn.metrics import r2_score
print('R-squared Score  : ',r2_score(y_test,y_pred))

R-squared Score  :  0.9936639083093958
```

B. Visualisation+Plotting



C. Predicting 30 Days Future Value



Conclusion

We propose a RNN and LSTM based model for stock price prediction. We trained the model using the data of Apple. We also used the sliding window methodology. Our result came out to be very accurate. Our RMSE and R-squared values were very small indicating the minute difference between predicted and test values.It's possible that fluctuations in the stock market don't always follow a predictable pattern or the same cycle. The existence of trends and their duration will vary depending on the firms and sectors. The analysis of these kinds of cycles and trends will increase investor returns.

IV. Future Work

To delve deeper into the working of the models used, i.e. Sequential, Dense and Stacked LSTM, we can also apply accuration model. This will give us more accurate results for the same dataset, and hence also help us in understanding the working of the Stock Markets better. We can also apply various other methodologies like CNN, Resnet- M, FLASK, Prophet models, etc. We can also delve deeper into using various normalisation techniques, result calculation parameters, etc.

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