TIME SERIES ANALYSIS OF STOCK PRICE PREDICTION USING HYBRID DEEP LEARNING NEURAL NETWORK

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This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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APPROVAL

This Project titled "TIME SERIES ANALYSIS OF STOCK PRICE PREDICTION USING HYBRID DEEP LEARNING NEURAL NETWORK", submitted by Jannatul Ferdaus Lemu to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 28th January 2022.

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DECLARATION

I hereby declare that, this project has been done by me under the supervision of Ms. Nazmun Nessa Moon, Associate Professor, Department of CSE, Daffodil International University, Dhaka. I also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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ABSTRACT

The motive behind researching on "TIME SERIES ANALYSIS OF STOCK PRICE PREDICTION USING HYBRID DEEP LEARNING NEURAL NETWORK" is to explore the thoroughness of the historical financial data of a stock suffice to make cabbalistic foreboding about its aspect prices with the use of Machine Learning. The purpose of my task is that, as the price of a stock fluctuates with time dimension, it is occupied to go through with specific patterns which I prospect to capture using Deep Learning and utilize for future predictions. At first, I will amplify on the necessary of theoretical background information regarding Machine Learning , concentrating on particularly the neural networks that will later be used. Pursuing that, I will experiment that how existing research about stock market forecasting using corresponding techniques prosecuted in the past and I will propose a model in this research using Hybrid Long short-term memory (LSTM), a Recurrent Neural Network architecture which is the most suitable method for this kind of analytical tasks. I have worked with around 1132 data which were collected from online platform. Here, I have analyzed error fluctuation of the collected data through one proposed model rather than analyzing the result of different model accuracy. At last, I will try to make predictions about the future trajectories of the stocks' prices and draw consequences from them.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Prognosis of future intercourse structure of stock prices has been an extensively area of research. Some people confide about prophesying of the stock prices, there are also have propositions which is demonstrated as if it is correctly formulated or modeled, the accuracy level will be high of stock prices prediction. The latter school of thought given attention of developing the robust statistical, econometric, and machine learning models based on the variables and appropriate functional forms. There are narrations in the literature that for forecasting future values of stocks, they only focused on time series analysis and decomposition . In this regard, several sentiments have declared for stock price forecasting by following a time series decomposition approach. These approaches provide the user with visual expositions of the indicators which help the ordinary investors to understand the ways of stock prices movement. In this research, I have proposed a granular approach towards forecasting stock price movement pattern by exploiting LSTM techniques. I believe this approach will help the investors in the stock market who are specifically interested in short term investments and achieve profit. Moreover , I have presented a predictive framework that multitude ramifications and regression using a long-and short-term memory (LSTM)-based advanced deep learning model. The dynamic stock price marketing is riskier because of its high volatility. The volatility hypothesis is a very challenging task.Thus, a perfect stock predicting model is one of the most hot research area. An accurate prediction model can be helpful for an investor to achieve targeted profit. Most recently, technical abilities and significant data have been calculated for identifying the trend of stock prices. A mathematical formula can represented as technical indicator. Therefore, in this work, I have considered technical indicators for identify the trends of stock. Technical indicators such as moving average, Bollinger bands, RSI, and MACD are most common to use. However, here an artificial-neural-network (ANN) based diagram is considered for stock price forecasting. In addition, ANN was invented by the inspiration of a biological neural network, where performing tasks of each neuron selects the input as stock price data. On the other hand, nonlinear functions such as sigmoid and rectifier units is computed as the output of neurons. A hybrid neural network (LSTM) is deliberated to predict stock price indices. The original subseries of time series divided by using LSTM algorithm to build a training and prediction model for each sub series. The sum results of all estimated sub series was combined as final prediction results. This new critical LSTM model are very robust for nonlinear data.

1.2 Motivation

Artificial Intelligence (AI), It sounds like innovative magics is happening around the whole world and also inside our human brain . It has became a momentous technology which applied in the automatic cars, intelligent robots, image and speech recognition, automatic translations, and medical assistants sector . Hence, different machine learning methods has been a significant issue in financial and economical section. Consequently,over the decade , the researchers come up with creative predictive ideas. Researchers are working hard for the betterment for predicting the stock prices more accurately . By utilizing the methods , shareholders and investors can make plans and strategical approaches without any hesitation for taking action towards investments . This leads the organizations or any individual investor to get any predictive method that ensures them handsome amount of money from their business easily along with less investment risk. In finance, stock market forecasting is thought as one of most competitive tasks to attempt till now because of the stochastic behaviors and complex dependencies of it . The unpredictable nature of the stock market is the foremost reason for existing no certain models of machine learning which can precisely forecast about stock market and also there is more things to perform in this sector which is the most inspiring factor for me to research and build a better predictive system with accuracy.

1.3 Statement of the Problem

Because of the market volatility, the prediction of stocks specifies , it is a very arduous manner which depends upon a proper forecast model.An investor's decisions effects the fluctuation trend of the stock market inconsistencies. The stock market prices are rising at dynamic stage and susceptible to fast changes. The reason behind it is underlying perspective of the financial domain which can also be imposed to the composition of the various unfamiliar parameters. These parameters comprises previous day closing prices, ratio and the other unknown factors as like the economy, election results, and rumors. Using machine learning there have been manifold efforts to predict stock prices. The navel of each research method can switch in three distinguishable ways:

1- The targeted price can be changed in near-term which is less than a minute, short-term, means tomorrow to a few days later, and lastly long term which is considered months later.

2- The set of stocks in a particular industry ,branching to all general stocks.

3- A global news and economy trend can be used as the predictors range, to specify the characteristics of the company, and finally to entirely time series data of the stock price.

The contingent stock market forecasting target can include the future stock price, the volatility of the prices, and market trend. In the stock market prediction , only two types are common that include a sculpture prediction and a real time prediction which is used in the stock market prediction system. In sculpture predictions, for predicting the future price of shares by calculating the average price,there is a defined set of rules. In the real time predictions, there is a compulsory to analyse the internet and monitoring of the current price of shares of a company.

1.4 Research Questions

First attempt is I need to analyse correct questions to find out the accurate answers. I have tried to find the answers of observable points that are given below:

1. How much popularity of Machine Learning have in price prediction sector ?

2. What are the limitations faced while predicting price ?

3. How many models and methods can be applied for price prediction?

4. By using deep learning approach , using different features is it possible to gain detailed forecast stock values ?

5. How the expected prices of stocks be used and how it will affect the investor?

6. How solution for such problems can be formulated?

1.5 Research Methodology

This paper will explore the financial data forecasting programs where a data set will be storing all historical stock prices and this data will be considered as a formulated set for the program. The chief aim of the prediction is to reliably and more accurately reduce the score of uncertainty associated with investment argument making in the stock market. The proper result can give an idea about the stock's future price based on the prediction made by the algorithm. In this segment, my workflow and data refinement is described elaborately. Besides, I have also narrated about data cleaning, attribute segment. Training models and employing the models are explained as well. I have also give the visualization about the outcome of the algorithms. Moreover, here I created a model which is based on Hybrid LSTM networks for predicting the stock price activities for input number of historical stocks. It analyse data on daily basis by scrapping data from the data sheet which is linked with google drive ,after that it attempted to create a demo price graphical representation for each segment and assume the next day price of the stock which compares the demo stock price with the actual stock price. On the other hand, in Sentiment analysis data collection is as same as LSTM scrapping method. Here I extract around 1132 historical data by using the language of python script. Finally, I justified the next day stock price prediction using Hybrid LSTM method.

1.6 Objectives

There are much more to gain from machine learning in the sector of forecasting the stock price . The objectives of my work are given below:

Economic Objectives:

1. Predict the price of stock

2. Rising the usage of Machine Learning in composing economic state

3. Decrease the risk of stock market fragility

Technical Objectives:

1. Search the best selection idea for further use in such cases

2. Find the best algorithm for price prediction

3. For building a model for stock market, this approach depends on the LSTM deep learning approach.

4. Stock market historical data will be tested and trained using LSTM method.

5. To analyse the model based of RMSE principles , it have to carry preparation and research on the basis of LSTM evaluation techniques.

1.7 Research Layout

- **Chapter 1:** Introduction: It includes the introduction, motivation, Problem Definition, Research Question, Research Methodology and objectives.
- **Chapter 2:** Background: A small discussion about time series prediction and applying ideas of time series of creating a better stock market prediction system.
- **Chapter 3:** Methodology : Techniques of Hybrid LSTM that are used in time series analysis.
- **Chapter 4:** System Implementation and Result: Describe about how the techniques are applying on the stock market data-sets and also have the representation about the outcomes.
- **Chapter 5:** Conclusion and Future Scope: Short discussion of the time series analysis and about the issues which can be included in future work to create the system more perfect.
- **Chapter 6:** Exhibits all the references studied for this research.
- **Appendix**

CHAPTER 2

BACKGROUND

2.1 Related Works

For many years stock market forecasting played a vital exertion towards our business and finance. Accurate prediction is very significant for the investors to determine if it would better to buy or not. There have been a monumental number of researches done by many enthusiasts who previously established prediction ideas which is intent to achieve more accuracy. Artificial Neural Network based prediction is the first technique for the stock market trend prediction. As per to Wong, Bodnovich and Selvi [8], the most rapid Neural Network applications in past 10 years are in the sector of production around 53.5 percent and in finance it is arround 25.4 percent. In finance, neural network have the most rapid solicitation in stock performance and selections secto. Thus, it can be significantly used in stock markets, to predict either stock prices or stock returns. However, NNs need large number of previous history[3][9] and the best network architecture is still unpredictable [5]. Sometimes, reliability results of complicated networks may decrease [9]. Labiad, B., Berrado, A., Benabbou, L. (2016) did an analysis on Moroccan Stock Exchange for Short Term Stock Movements Classification and found 89% accuracy in shortest CPU time [4]. They had included Random Forests, Gradient Boosted trees and Support Vector Machine (SVM) techniques. They applied technical indicator as input variable. After that, they added selection feature to improve prediction accuracy. This experiment present us higher accuracy in RF and GBT techniques than SVM. A hybrid neural network VMD-LSTM [11] considered to predict stock price indices. LSTM creates a prediction model including training of data for each subseries and VMD algorithm divides the original time into subseries . The sumation of estimated subseries was gathered as a final prediction results. Jing et al [12] proposed a hybrid model which includes deep learning and sentiment analysis for Chinese stock market. The hybrid model integrates LSTM for stock prediction with sentiment analysis. Senapati et al [13] given a hybrid model of prediction using ADALINE neural networks and modified particle swarm optimization (PSO). Kim et al. [14] created a long short-term memory (LSTM) model that includes

LSTM and GARCH-type models to predict stock volatility. It creates a self-loop to generate a path which can flow repeatedly for a long time. DNN [15,16] is better than conventional machine learning techniques when it comes to solve nonlinear problems. By using the PSR approach, a DNN-based prediction model is developed and it predict stock price movements. Aditya Gupta and Bhuwan Dhingra used another stock market prediction technique in 2012 [1]. Hidden Markov Models (HMM's) have been applied in their work. They have analyzed historical data of different stocks to predict the next day's stock values usiny Maximum a Posteriori HMM approach. HMM's has also a successful journey in the sector of analyzing and predicting time depending phenomena, or time series [2]. After examining their approach , they compared the results to some of the existing ideas using HMMs and Artificial Neural Networks using Mean Absolute Percentage Error (MAPE).Depending on these models, there exist some draw backs,most significantly the conventional time arrangement models. The cost of stock can be influenced by countless components, for example, economic situations and natural impacts. Moreover, these models just accept the previous collected data information as there data factors, however it does not think about the effects of the condition of the stock on the prediction, for example, the enthusiastic inclination of financial specialists. Therefore, as observation finish, the long term dependence issues are not very significant. As recurrent networks can not handle long sequences data, S. Hochreiter and J. Schmidhuber, preached with LSTM[17].In my research work I have visualized an idea on LSTM system by utilizing input values as historical data to calculate the activity of stock price. I use a dataset as quite huge range of technical indicators and embed LSTM method to get the accurate prediction rate. The main purpose of this paper is to forecast prediction system of stock market using Hybrid LSTM.

2.2 Bangladesh Perspective

The economical condition of Bangladesh is not stable at this very moment time. Due to COVID-19 pandemic , the economy of our country has been enduring much. If any other factors start behaving to create it more nondescript, it could carry us towards the economic disaster. So I must endeavor my best to keep other variables as stable as possible that can play a good effect on the economy. Moreover, stock price is deeply associated with the economy of a country. The government is trying hard to carry necessary steps to keep all the other multiplicator in control. If the price of stock or share market can be predicted, then the government can easily be able to ensure the necessary steps to control the stock market which will be in favour of our country.

2.3 Neural Networks

Artificial Neural Networks (ANNs) is basically designed with the intention to copy the architecture and characteristics of the human brain, also recreating its ability to fast processing system and learning information. While advance technologies are coming in, the original links between these two is, the fundamental idea remains that both human brains and ANNs learn by example and improve over time. The basic unit of computation in both is the neuron, often called a node or unit in ANNs. Below showing the Curriculum between BN and AN in figure 2.1,

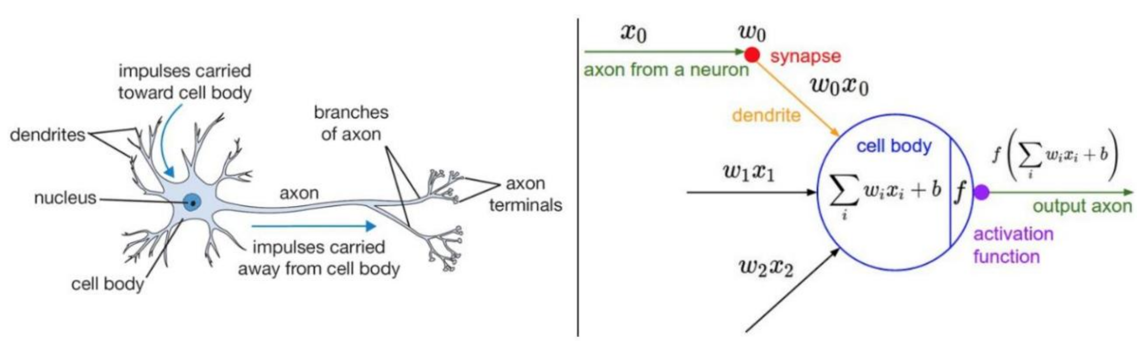

Figure 2.1: Brain Neuron (left) Compared to Artificial Neuron (right) [22]

2.4 Deep Neural Networks

Applying an LSTM neural network approach to train models at predicting stock , this particular section will give a basic explanation of the LSTM's superclass, deep neural network activity . In deep neural networks, each layered node is known as a neuron, and and there have more than two layers of neurons. Let me begin with what the neuron does. A neuron is a function that takes one or more inputs to produces an output. For each input, xk , the neuron multiplies it with a weight, wk . This weight shows the strength of the connection between the neuron and the neuron that emitted the input. After having the result of multiplied inputs with the weights, they get summed up as such :

Inputs: $\vec{x} = (x_1, x_2, \ldots, x_n)$

Weights: $\vec{w} = (w_1, w_2, \ldots, w_n)$

Sum: $s = \Sigma(x_1 w_1, x_2 w_2, \ldots, x_n w_n)$

A neuron also holds a bias which is a constant value. Some examples are sigmoid functions, which most often return values between 0 and 1. The input layer hold the initial data of neural network to pass the calculated results towards a hidden layer. Here, displaying the graphical visualization of sigmoid without and with bias sequentially in figure 2.2 and 2.3,

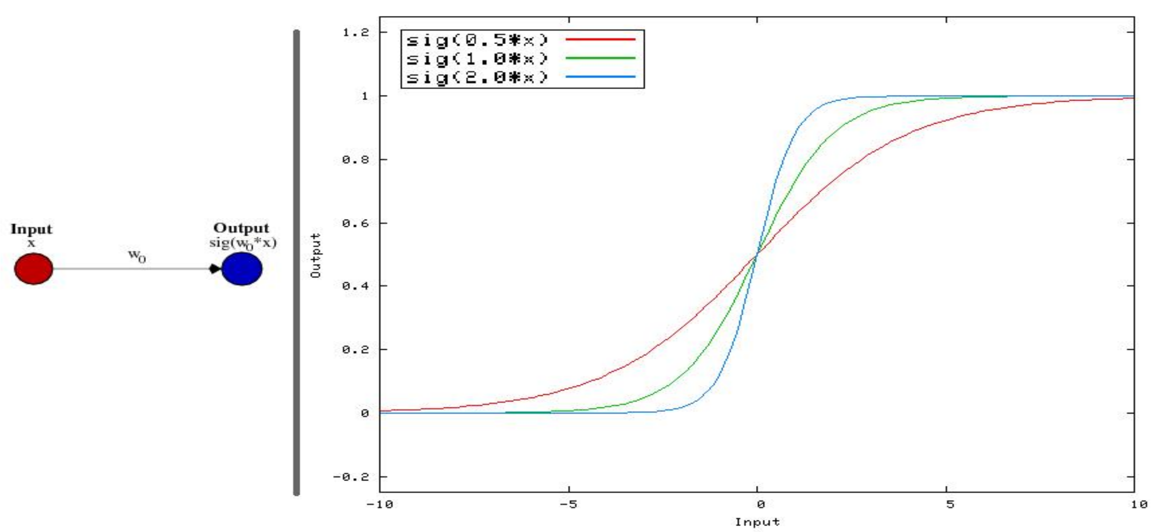

Figure 2.2 : A Sigmoid Neuron without Bias

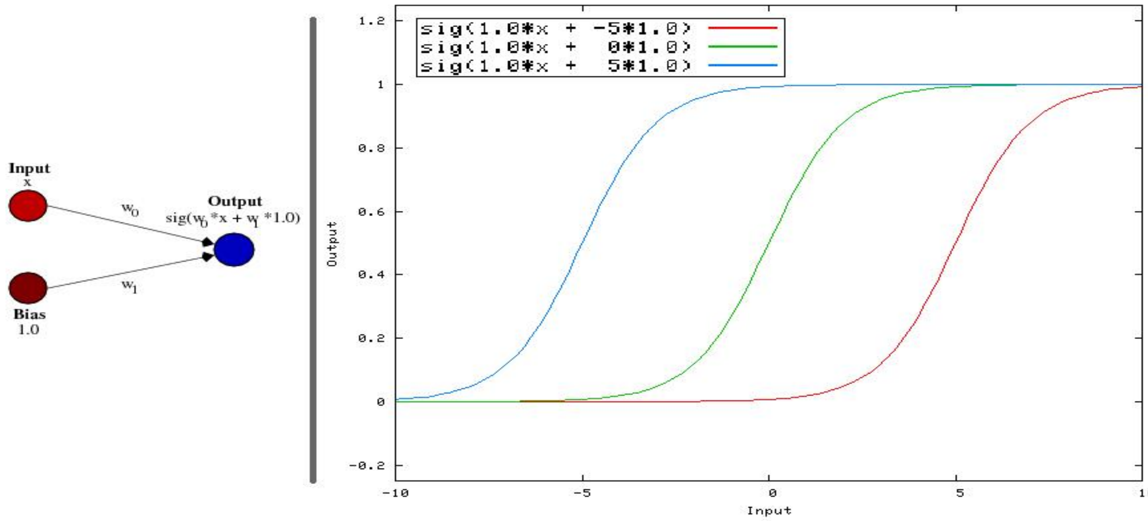

Figure 2.3 : A Sigmoid Neuron with Bias

2.5 Recurrent Neural Networks

We can go through the fundamentals about how DNNs work in the section 2.4. Though an LSTM is technically an instance of an DNN, it is more clearly called a Recurrent Neural Network (RNN) and it has many differing qualities which improve the forecasting capability of my models. The significant difference between RNNs and their super class, that is , RNNs are well-suited for sequential data ,because they can hold a hidden state, effectively a memory, and also the output of an RNN is not only a function of its input, but it always stay in hidden state. It allows the neural network to remember the past records and be used repeatedly over the time . For this reason, RNNs are more likely work as a directed list of “snapshots" of a neural network over time, and each of these “snapshots” can be referred to as an RNN cell.

2.6 Convolutional Neural Network (CNN)

Deep Learning is an efficient instrument for analyzing big data. By using complex algorithms and artificial neural networks data can be trained. Besides, A Convolutional Neural Network(CNN) is a type of artificial neural network and it is commonly used for object recognition. CNN plays a significant role in different functionality such as, image processing issues, computer vision localizing and segmenting, video analysis etc. So, here I propose a framework based on a hybrid deep learning which is a combination of a convolutional neural network (CNN) and long short-term memory (LSTM). The proposed hybrid LSTM model uses CNN layers for feature extraction by taking data from the dataset as input function with LSTM layers for sequence learning.

2.7 Time Series Analysis

Time series is a series of data points which are indexed in time order. Most commonly, a time series taken sequentially at successive level and equally spaced points in time. Thus it is a sequence of discrete time data. It is mathematically defined as a set of vectors x(T),T = 0,1,2,... where T represents the time elapsed that we can denote the observations by $Y_1, Y_2, \dots Y_T$. The variable x(T) is treated as a random variable. A time series is uni-variate whenever it contains records of a single variable. If it records more than one variable are considered, then it is called multivariate. Again time series can be continuous or discrete. If observations are counted at every instances of time then it is called a continuous time series. Such as, flow of river, concentration of a chemical process, temperature reading etc. can be recorded as a continuous time series. On the other hand, population of a country, production of a company, exchange rates between two different currencies may present discrete TS. The consecutive measurements are basically recorded in a discrete TS at identically spaced time intervals such as hourly, daily, weekly, monthly or yearly time separations. The variable audited in a discrete time series is occupied to be measured by the real number scale as a continuous variable. By merging data together over a tangibled time interval anyone can easily transform continuous TS to a discrete one. There are a number of significant interests in a TS such as Smoothing, Modeling, Forecasting, Control.

• S**moothing:** The observed Y_t are assumed to be the result of “noise” values t additively

contaminating a smooth signal t.

$Y_t = \eta_t + \varepsilon_t$

It may be wished to recover the values of the underlying η_t.

• **Modelling:** To develop a simple mathematical model which elaborate the observed pattern of $Y_1, Y_2, \ldots Y_T$. This model may depend on unknown parameters and these will need to be estimated.

• **Forecasting:** On the basis of observations $Y_1, Y_2, \ldots Y_T$,for predicting what the value of Y_{T+L} will be (L>1), and possibly to give a clue of what the uncertainty is in the prediction.

• **Control:** To intervene with the process which is producing the Y_t values in such a way that the future values are altered to produce a favorable outcome.

2.8 Components of Time Series

In general, a time series is supposed to be affected by only four main components. These components are: Trend, Cyclical, Seasonal and Irregular components. A brief narration of these four components is conferred here. The common tendency of a time series to increase, decrease or stagnate over a lengthy period of time is termed as Secular Trend or simply Trend. Therefore, it can be said that trend is a long term movement in a time series. For example, series relating to population growth, number of houses in a city etc. show upward trend, whereas downward trend can be observed in series relating to mortality rates, epidemics, etc.Time series fluctuates by seasonal variations within a year during the season. The significant factors causes seasonal variations, that are: climate and weather conditions, customs, traditional habits, etc. For example sales of ice-cream increase in summer, sales of woolen cloths increase in winter. Seasonal variation is also a momentous factor for businessmen, shopkeeper and producers for making proper future plans. The cyclical variation in a time series describes the medium-term changes in the series, caused by circumstances, which repeat in cycles. The longevity of a cycle extends over longer period of time, normally two or more years. Most of the economic and financial time series show some kind of cyclical variation. For example a business hoop consists of four phases such as I) Prosperity II) Decline III) Depression IV) Recovery. A typical business cycle is shown as irregular or random alternatives in a time series are caused by unpredictable influences which are not constant and also do not repeat in a particular pattern. These variations are caused by incidents such as war, strike, earthquake, flood, revolution, etc. There is no specific statistical techniques for calculating random fluctuations in a time series.

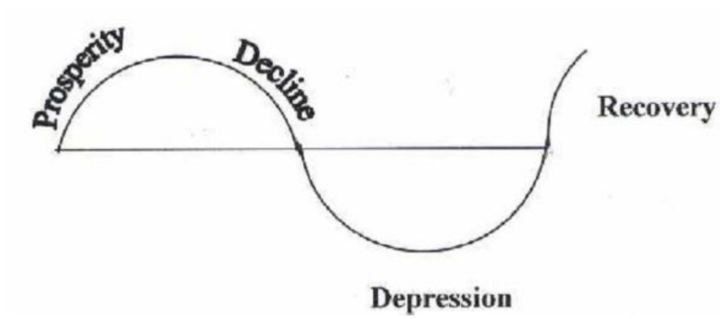

Figure 2.4: Four Phases Business Cycle [24]

Take into account the effects of these four components in figure 2.4, two different types of models are usually used for a time series known as Multiplicative and Additive models.

Multiplicative Model: $Y(t) = T(t)\times S(t)\times C(t)\times I(t)$.

Additive Model: $Y(t) = T(t) + S(t) + C(t) + I(t)$.

Here $Y(t)$ is the observation and $T(t)$, $S(t)$,$C(t)$ and $I(t)$ are respectively the trend, seasonal, cyclical and irregular variation at time t. Multiplicative model is based on the audacity that the four components of a time series are not being compelled to liberate and they can affect one another; whereas in the additive model it is occupied that the four components are distinct of each them.

2.9 LSTM (Long Short Term Memory)

A central distinction LSTM has versus traditional RNN’s is a gating tackle. An illustration that exhibits the variety in LSTM’s ability to save long term memory. This can give benefits in sequential tasks or natural language processing. This can be illustrated when there’s network propagate text given for a research. Then the RNN model has to produce the following word. Network generated text is forecast when information is given,for example, a name or object and the model after that it produce the same model or word when later predicting the next word. Since RNN’s commonly have an issue with having short term memory the average RNN is only able to exploit information from the text . Because of the issues of short term memory can provide some challenges to execute the models. This differentiate from a LSTM which is able to store information from prior periods of time that gives the better precision when propagate contextual information of predictions. The word of Long short memory (LSTM) for this perusal allude to a recently developed artificial RNN architecture to resolve the overflowing and vanishing gradient problems inherent in traditional RNN preparation [18]. In short, these are all the obedience in long term that cause issues when a cell is an issue.For a lengthy period of time,everything must be dispelled. In many situations, where the gradient can train a neural network using gradient-based learning methods and back propagation. It arrives a concern for finite-precision numbers as the computations are used in the obtainment. This is partially composed by LSTMs.However, the clause of having unvaried flow of gradients is a problem. A cell, an entry gate and the entrance gate make up the common LSTM unit [19]. The evaporated version of the revolved module in an LSTM is shown in Fig 4 below, where each module comprises four interacting layers instead of one (activation function) layer in a regular RNN. How data passes through a cell is showing in the architecture which is provided in the following paragraph.

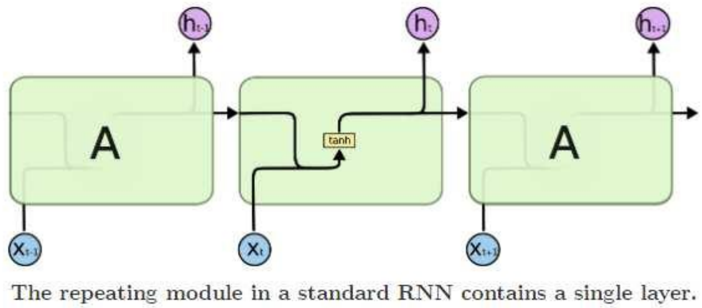

Figure 2.5: The Condensed Version of the Repeated Module in an LSTM [23]

In this figure's (2.5) top is Cell condition that is altered by the layers of the LSTM unit. The main sigmoid layer illustrate is what is generally referred to as the "forget gate layer," which looks at the external input in the repeated modules chain as well as from the inputs of the previous module and produces a variety of outputs from 0 and 1 for every level, in the network. This, In essence, the sigmoid layer specifies which numbers are remaining in the in conjunction with the following equation, the cell state and those that are eliminated:

$ft = \sigma(Wf * [ht - 1, xt] + bf)$

The up next move is to identify what new information is available. The recent input needs to be researched. Next, another sigmoid layer is the "data gate layer" that determines which variables to modify.In addition, a new matrix is created which is for constructing new party numbers, it could be added to the cell state. This vector is generated in Fig.6 through a layer of tanh. The cell state can be replaced by integrating between these two layers. As seen, this takes place through three distinct mathematical steps. Which is listed below:

$it = \sigma(Wi * [ht - 1, xt] + bi)$

After deciding the values to update, the candidate Vector is created:

$Cnew = \tanh(WC * [ht - 1, xt] + bC)$

Lately,the horizontal line would be able to update by the cell state indication:

$Ct = ft * \ Ct - 1 + it * \ Cnewt$

The final layer is consistent because of the choice of what gets from the cell, output. Again, the sigmoid layer dictates which beliefs continue and also which are discarded.

$ot = \sigma(Wo[ht - 1, xt] + b0)$

Moreover, the state of the cell passes through the layer of tanh prior to multiply it by the sigmoid production Layer such that the production stays with only the planned pieces.

$ht = ot * \ \tanh(Ct)$

Then the output value is fed into the next recurring value, in the module, the procedure is replicated towards the next layer in architecture.

2.10 Pros and Cons of LSTM

The advantages of LSTM are :-

- For making it recurring,it can model a collection of records where each pattern can be assumed to be dependent on the previous one.
- To extend the powerful pixel neighbourhood , it combined with convolutional layers.
- The main advantage of an LSTM is, its ability to learn context of specific temporal dependence. Where each LSTM unit recollect information for either a long or a short period of time without apparently using an activation function within the recurrent components.

The disadvantage of LSTM are :-

- It has Gradient exploding and vanishing problems.
- Training LSTM is a difficult task due to the way it is designed.

- It cannot be systemed as lengthy sequences .

2.11 Terminologies Used

Below there is presenting short summary of the various terminologies relating to my proposed stock prediction system:

1.Training Set :

Subsection of the original data is used to train the neural network model for forecasting the output values .

2. Test Set :

It is also a part of the original data which is used to make predictions of the output values, and also differentiate with the actual values to evaluate the performance of the model .

3. Validation Set :

Portion of the original data that is used to tune the parameters of the neural network model

4. Activation Function:

In a neural network, the activation function of a node defines the output of that node as a weighted sum of inputs.

5. Epoch

When it is necessary to know the behavior of different networks, epoch is the key. It deals with the model and is the indication of the data set that is fed to model only once. These datasets passed multiple times through a single network. Each time it operates with different updated weights and its goal is to get more accurate and better result. Gradient descent are used in different deep learning algorithms in diverse models. For a given number of epoch these Gradient descent calculates the gradient of the loss function as per the features for the training values. The number of the rounds of epoch is not fixed. For getting optimal weights several rounds of epochs required to create a model with the equivalent data set. Distinctive datasets show the various conduct ,as a result different epoch might be prospected ideally for preparing their systems supremely.

6.Batch Size :

The number of samples that must be processed by the model before updating the weights of the parameters .

7.Error

During the training of my proposed models, there will be noticeable use of a concept called error. The loss is a score that tells how good my proposed model is performing its task [20]. The destination of it is to minimize the loss in a model, as a lower loss means that the model is better at the task. Several loss functions can be used, and which one need to choose largely depends on the task, besides, which one wants to use the neural network for.

8.Root Mean Square Error

The standard deviation of the spillover is described by Root Mean Square Error (RMSE) .RMSE is used for inspecting the productivity of the model. For proper utilization of RMSE value, the contrast between the target and the acquired output value can be minimized.Furthermore, RMSE is the square root of the mean average of the square of all of the error. RMSE is the standard deviation of the excess.The regression line data points are defined through the measurement of residuals. The utilization of RMSE is exceptionally normal and it makes a magnificent broadly useful blunder metric for numerical forecasts. For verifying experimental result RMSE used as common tool such as in climatology, future estimation, and regression analysis[21].RMSE intensifies and seriously rebuffs enormous mistakes like Mean Absolute Error.

$$\mathrm{RMSE}_{fo} = \left[\sum_{i=1}^{N} (z_{f_i} - z_{o_i})^2 / N\right]^{1/2}$$

9. Mean Absolute Error

Mean Absolute Error calculates the average difference between the calculated values and actual values.Scale-dependent accuracy calculates its error in observations taken on the same scale. Evaluation metrics is used for regression models in machine learning. It counts loss between actual values and values forecasted by the model. It is conducted to predict the accuracy of the machine learning model.

$$\text{Mean Absolute Error} = (1/n) * \sum|yi - xi|$$

CHAPTER 3

METHODOLOGY

3.1 Stock Prediction Algorithm

Input: Historical Stock Price Data

Output: Prediction of stock price in the based on stock price variation

1. Start.

2. Stock data is taken and stored in a numpy array of 3 dimensions (N,W,F) where:

- N is number of training sequence.
- W is the length of sequence.
- F is the number of features of each sequence.

3. A network structure is built with dimension where there is 1 input layer, *a* neurons in the next layer, *b* neurons in the subsequent layer and a single layer with a linear activation function.

4. Train the constructed network on the data.

5. Use the output of the last layer as prediction of the next time step.

6. Repeat step 4 and 5 until optimal convergence is reached.

7. Obtain predictions by providing test data as input to the network.

8. Evaluate accuracy by comparing predictions made with actual data.

9. End.

3.2 Flowchart

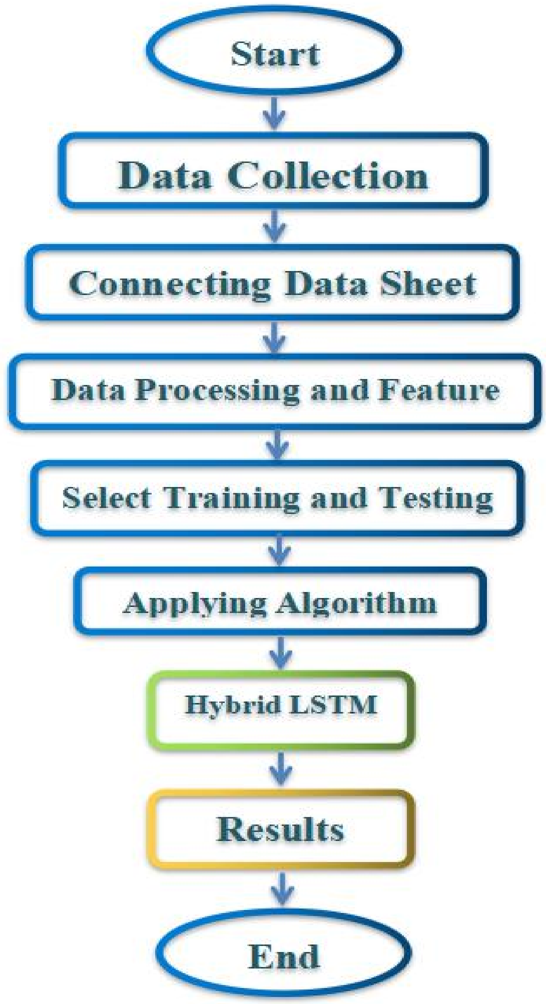

Figure 3.1: The Flowchart of Working Process

3.3 Proposed Model

```
[9]  # Proposed Model
     model = Sequential()
     model.add(Conv1D(filters = 16, kernel_size = 3, padding = 'same', activation = 'relu', input_shape = (1, window_size)))
     model.add(Bidirectional(LSTM(units = 16, return_sequences = True)))
     model.add(LSTM(units = 16))
     model.add(Dense(units = 1))
     model.compile(loss = 'mean_absolute_error', optimizer = 'Adam')
     model.summary()
```

Figure 3.2: Hybrid LSTM Model

3.4 Software

The data set are prepared and organized in Python, This model use lots of packages like numpy and pandas. A powerful library keras is used for developing the whole model . Dense layer is used for extracting featured data and LSTM used for supervised learning of featured data.

3.5 Technical Indicators and Features

From online platform, the following data points and technical metrics were gathered

1. Daily stock open price

2. Daily stock High price

3. Daily stock Low price

4. Daily stock Close price

5. Daily stock volume

My priority was the technological research component to process data set. The Open price and Close price columns represent the original and final price showing in the data set. In reality,the stock exchange took place on that day. The low price, high price columns represent minimum and maximum share price for a given day. And the last segment is Complete Trading Value, the number of shares registered on the day of purchase / sale. To train the model using open, high, low, and close price many experiment were executed as the input for the network and I have found the best results by using the high price as primary factor cause by developing the algorithm, the primary evidence points indicator (row) in the time sequence.

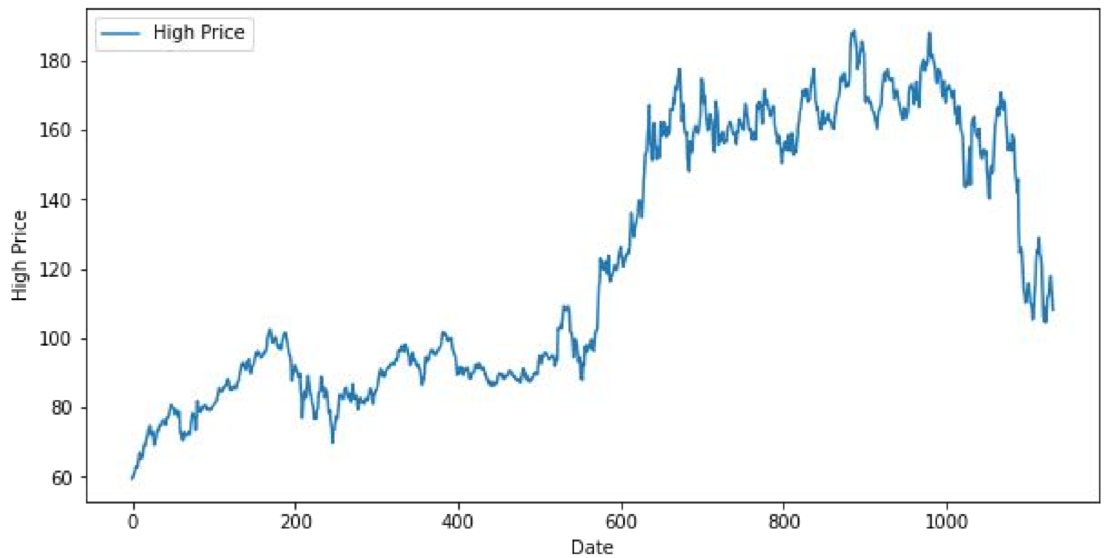

Figure 3.3 : Data Frame of High Price

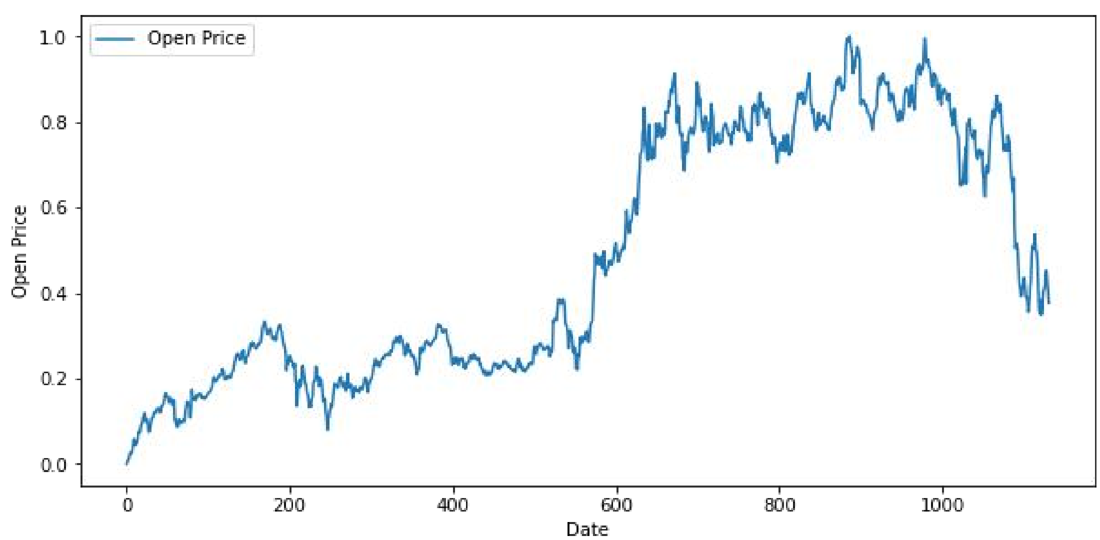

Figure 3.4: Data Frame of Open Price

3.6 Time Series Visualization

To identify temporal structures ,plots of the raw sample data can provide valuable diagnostics, like trends, cycles, and seasonality which can influence the choice of model. There are 6 variety of visualizations which can be used on my time series data. They are:

Line Plot: The first, and perhaps most popular, visualization for time series is the line plot. In Fig 3.5**,** time series is shown on the X-axis with observation values along the Y-axis. For visualizing the Minimum Daily Temperatures data-set is directly used as a line plot.

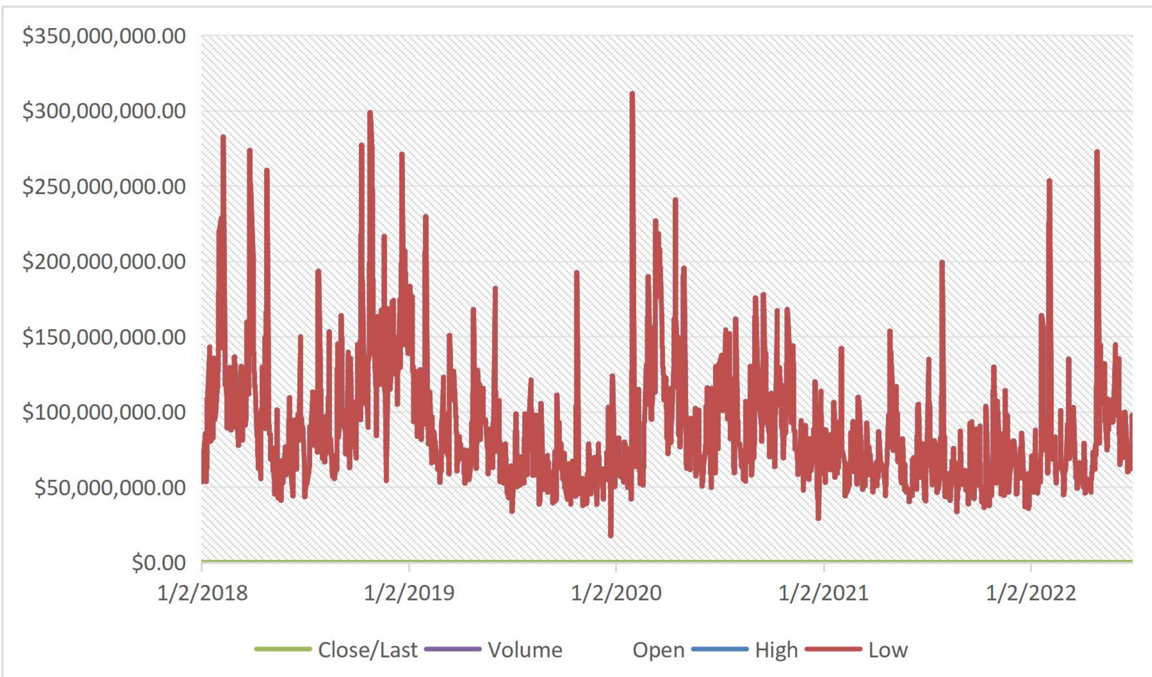

Figure 3.5: Line Plot of Data Sheet

CHAPTER 4

SYSTEM IMPLEMENTATION AND RESULT

4.1 Data Gathering and Preprocessing

A database is compiled for training and testing predictive algorithms. Minimum deviation of the database should be given and normal behaviour should be accounted. It was very important to choose a time frame where the stock market did not present any sudden jump or dip in prices. Often there are times of economic collapse in certain sectors, industries and countries. The extent of these type of collapses might not be foreseen or predictable. LSTM model was built in Python, using Colab environment which is an online compiler allows the user to import specified key figures and export them directly as CSV (comma-separated values) files.The data set includes one-day data points, each of the points includes the metrics of such data as stock daily opening price, stock daily closing price, stock daily high price, stock daily low price, and the volume of stock trading. In this stage it cleans data by removing the incorrect, incomplete, improperly formatted, or duplicated values.Sentence of splitting module : Sentence splitting modules with splitting the prepossessed data in different section. These data are collected for testing purpose in a text document. Whenever it completes its task, the pre-processed data handed to next step. For example, in figure 4.1, the data set is collected from the online platform stock market history , here I am using AMAZON historical stock market data . There I have worked with about 1132 data. Below there also showing the flow chart of data training process in figure 4.2.

	A	B	C	D	E	F
1	Date	Close/Last	Volume	Open	High	Low
2	6/30/2022	$106.21	97679400	$108.11	$108.18	$102.52
3	6/29/2022	$108.92	66375340	$107.38	$110.99	$106.91
4	6/28/2022	$107.40	75172030	$113.50	$114.85	$107.04
5	6/27/2022	$113.22	62133240	$117.09	$117.98	$112.70
6	6/24/2022	$116.46	69867620	$112.38	$116.71	$111.43
7	6/23/2022	$112.44	64345300	$110.39	$113	$107.93
8	6/22/2022	$108.95	60040130	$107.43	$112.13	$107.02
9	6/21/2022	$108.68	70901250	$108.20	$111.63	$103.56
10	6/17/2022	$106.22	99772150	$102.80	$106.98	$102.51
11	6/16/2022	$103.66	82186300	$104.47	$104.58	$102.01
12	6/15/2022	$107.67	85011060	$103.86	$109.06	$103.53
13	6/14/2022	$102.31	69728760	$104.19	$104.88	$101.43
14	6/13/2022	$103.67	99277740	$104.19	$106.54	$101.86
15	6/10/2022	$109.65	87412250	$113.42	$114.50	$109.05
16	6/9/2022	$116.15	67029840	$119.99	$121.30	$116.10
17	6/8/2022	$121.18	64926590	$122.61	$123.75	$120.75
18	6/7/2022	$123	85156710	$122.01	$124.10	$120.63
19	6/6/2022	$124.79	135269000	$125.25	$128.99	$123.81
20	6/3/2022	$122.35	97603320	$124.20	$124.40	$121.05
21	6/2/2022	$125.51	100560680	$121.68	$125.61	$120.05
22	6/1/2022	$121.68	127528980	$122.26	$125.18	$120.62
23	5/31/2022	$120.21	144634160	$116.28	$121.99	$115.68
24	5/27/2022	$115.15	93660160	$113.55	$115.19	$112.63
25	5/26/2022	$111.08	93002600	$107.97	$112.67	$107.45
26	5/25/2022	$106.78	93120100	$103.66	$108.18	$103.65
27	5/24/2022	$104.10	102934680	$104.03	$105.40	$101.26
28	5/23/2022	$107.56	107797360	$108.46	$108.82	$103.95
29	5/20/2022	$107.59	99500640	$109.57	$109.90	$105.01
30	5/19/2022	$107.32	88142540	$106.28	$110.03	$106.19

Amazon

Figure 4.1: AMAZON Historical Data from Online Platform

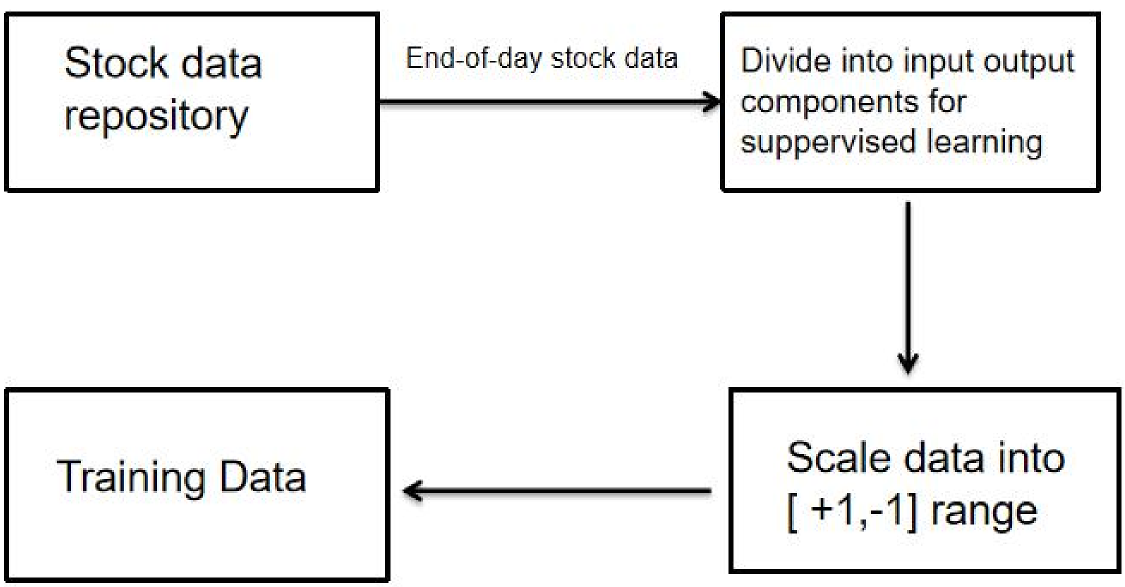

Figure 4.2: Data Preprocessing

4.2 Training Data and Window

In supervised learning, I have use labeled training data, typically a vector of pair values: an input accompanied with the desired output for it. Here, the data consists of float values of stock prices for various consecutive dates . It is noticeable that here, I have assume only having a single price feature for my stocks (e.g. “High Price”) .Furthermore, the exact same methodology can also be applied when having more features. A single price in itself does not contain enough information to predict anything meaningful.Windows needs to be introduced. Simply , a training window is enough but a fancy term refer to a vector of values as single input during the training. To expand on this, I have first make sure that my data points are in order that means sorted by date from oldest to newest and then I define a fixed size for my training window which I will be call by coding variable later . Following that condition, at first I get the oldest stock prices and insert them into a vector which becomes my first training input. The second one includes an equal number of stock prices, but this time starting from and ending with assuming that my stock prices exist in a zero-indexed array named with size . Similarly, the next training input will be the vector with the values until it contains the price of the last one .After this procedure, I am left with an array of input vectors but, as I have previously mentioned an output label which can sort any kind of training data, the structure of which will be my next target. The input data is normalized for feeding in the first propagation phase and the network is into the input nodes by using the formula:

$$v' = \frac{v - minA}{maxA - minA}(new_{maxA} - new_{minA}) + new_{minA}$$

Here,

V‘‘ = Normalized Input.

V = Actual Input.

Min A, Max A = Boundary values of the old data range. New minA, New maxA = Boundary values of the new data range. In this fact, it is -1 and 1 because the back propagation can only handle data between – 1 to 1.

4.3 Training Labels

Here, mainly presented two angles to examine. For providing the values information inside a training window , we need better prediction capability. Some patterns is behind the institution which is appeared with the prices in a single window which is contributed as such, if they were supposed to reappear in my test set. The first and simpler approach towards the single value is to follows a window as its output. Generally, a window's values would have the single value as like its output. Following the way, I have created a vector for all outputs which is combined with the training window inputs, and also comprised my training data set. Below showing the process in figures sequentially 4.3, 4.4, 4.5, 4.6 and 4.7 .

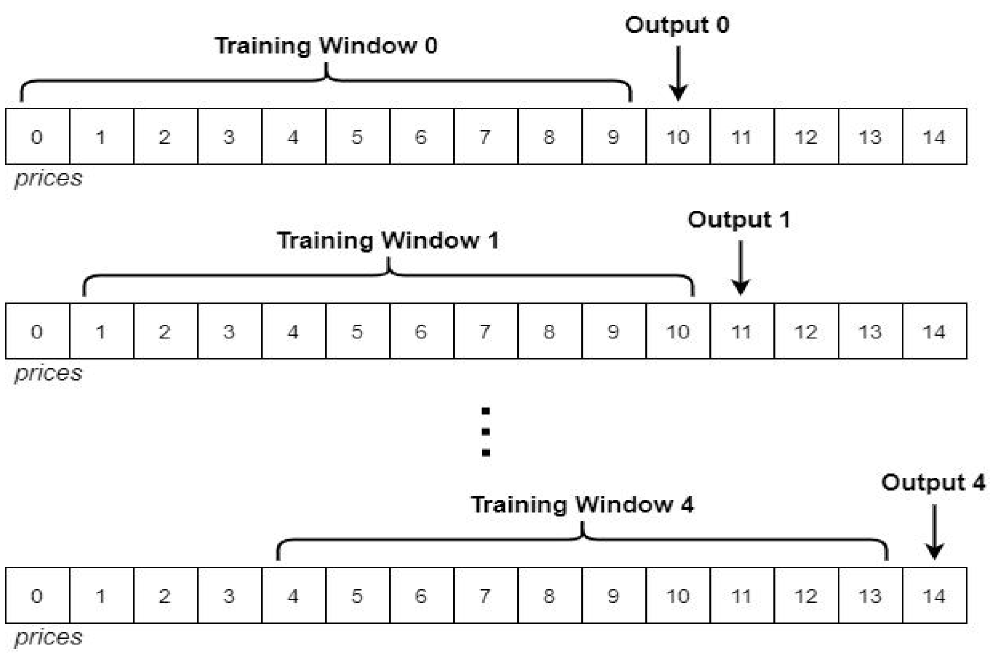

Figure 4.3: Training Windows with Single Outputs

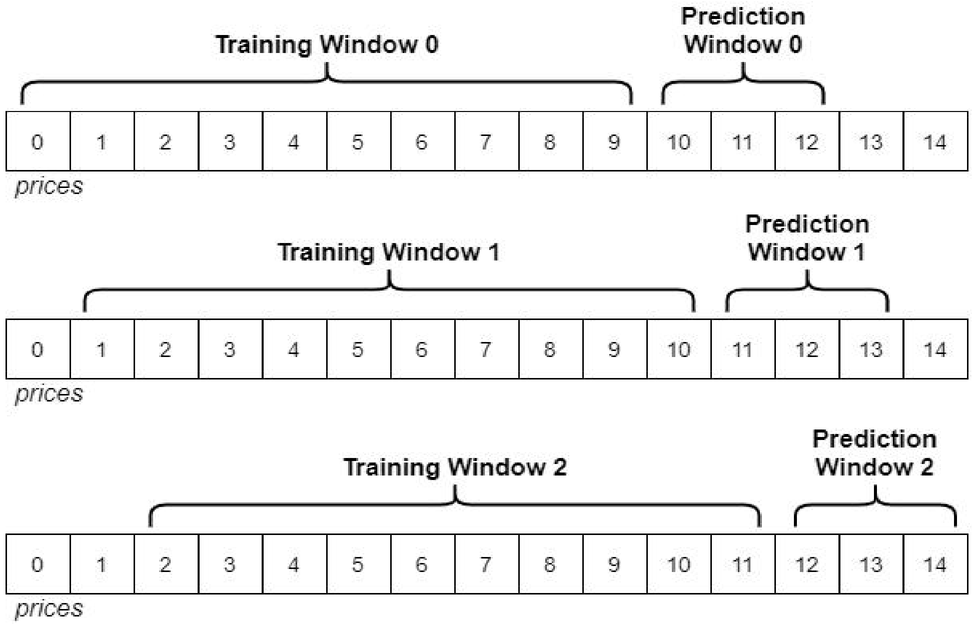

Figure 4.4: Training Windows with Prediction Window

```python
# Split Data into Train Set, Validation Set and Test Set
test_size = 127
validation_size = 127
train_size = len(dataset) - validation_size - test_size

train = dataset[0 : train_size]
validation = dataset[train_size : train_size + validation_size]
test = dataset[len(dataset) - test_size : len(dataset)]

print(train_size, validation_size, test_size)
```

Figure 4.5: Data Training , Validation and Testing

```python
# Convert an array of values into a dataset matrix
def create_dataset(dataset, window_size):
  dataX, dataY = [], []
  for i in range(len(dataset) - window_size):
    dataX.append(dataset[i : (i + window_size), 0])
    dataY.append(dataset[i + window_size, 0])
  return np.array(dataX), np.array(dataY)
```

Figure 4.6: Converting Array of Values into Data Set Matrix

```python
# Reshape into X=t and Y=t+1
window_size = 7
trainX, trainY = create_dataset(train, window_size)
validX, validY = create_dataset(validation, window_size)
testX, testY = create_dataset(test, window_size)
```

Figure 4.7: Reshape Window Size

4.4 Results Analysis

```python
plt.figure(figsize=(10, 5))
plt.plot(history.history['loss'], label = 'Loss')
plt.plot(history.history['val_loss'], label = 'Val Loss')
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()
plt.show()
```

Figure 4.8: Labeling Loss and Epochs

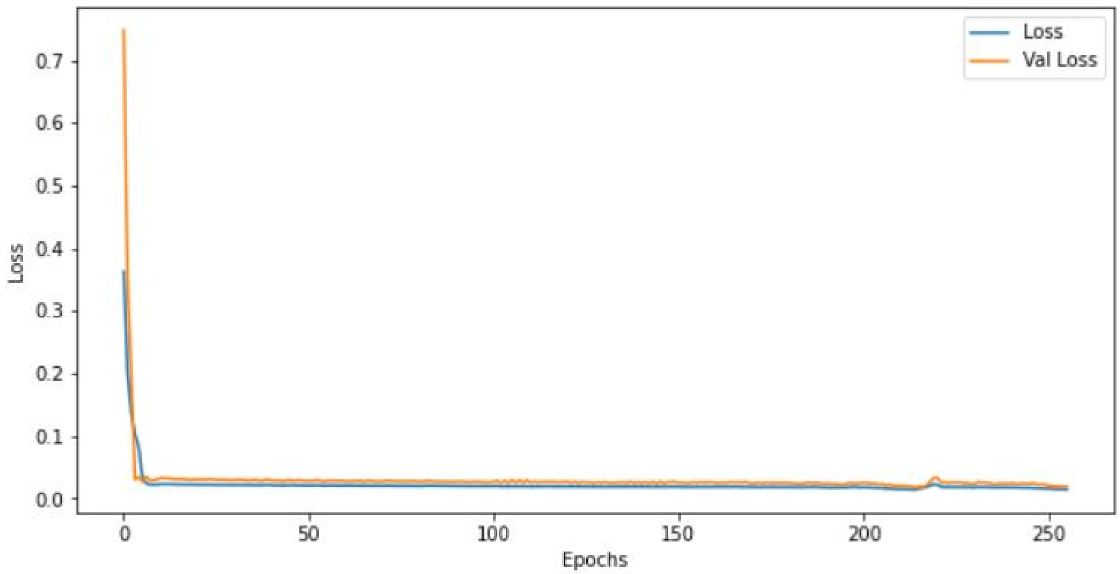

Figure 4.9: Model Loss

Here, it can be pointed that all predictions have very similar in “shapes”. Evidently, in training period of data, for making the model learned an average trend that stock prices intend to follow and utilize to every prediction, here, different predictions results only differentiating the y-axis based on the input test data, while it is storing an most identical shape. Using the results ,this method represent the above graphical presentation, according of the number of epochs and various different values for other parameters. Besides, such outputs vary significantly from what I was trying to accomplish and I have shown it in figure 4.8 and 4.9 . After this process trained data results are showing below in figures 4.10, 4.11 and 4.12 .

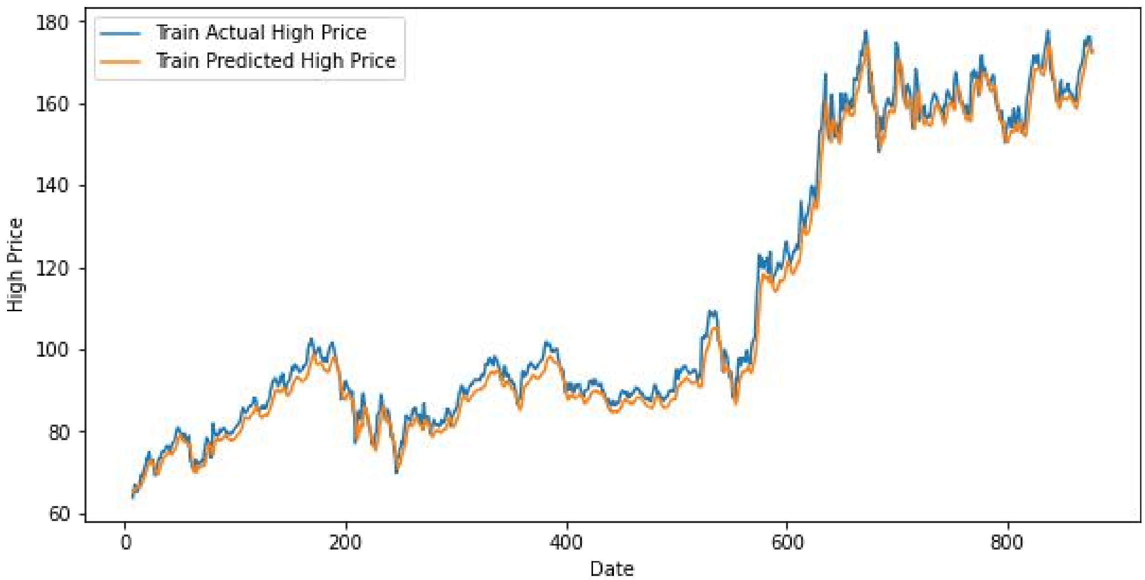

Figure 4.10: Training Plot of High Price

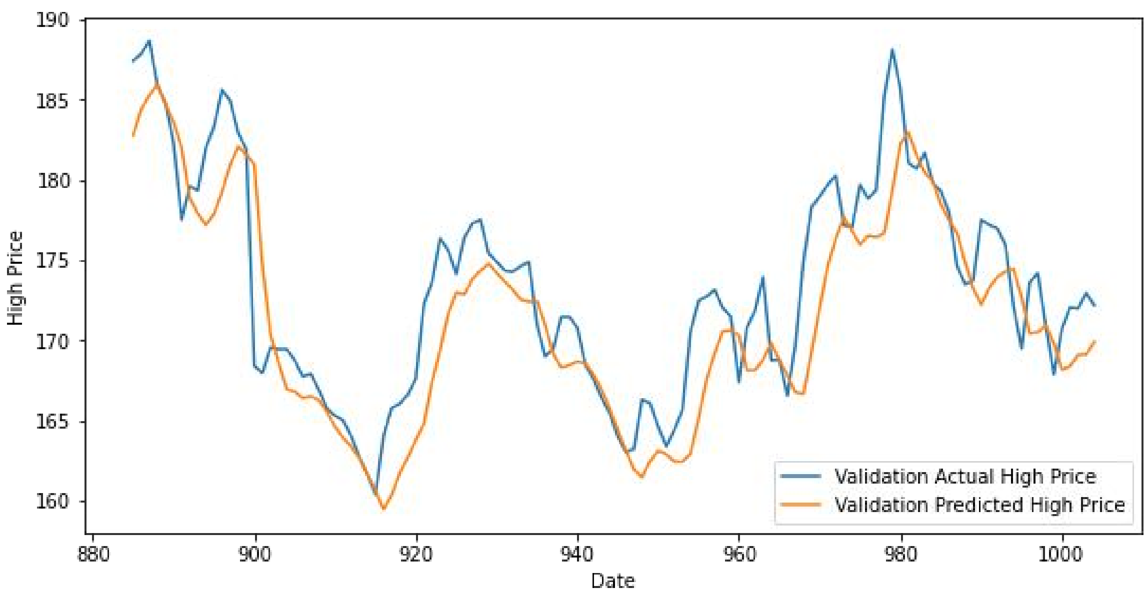

Figure 4.11: Validation Plot of High Price of the Amazon Stock Market

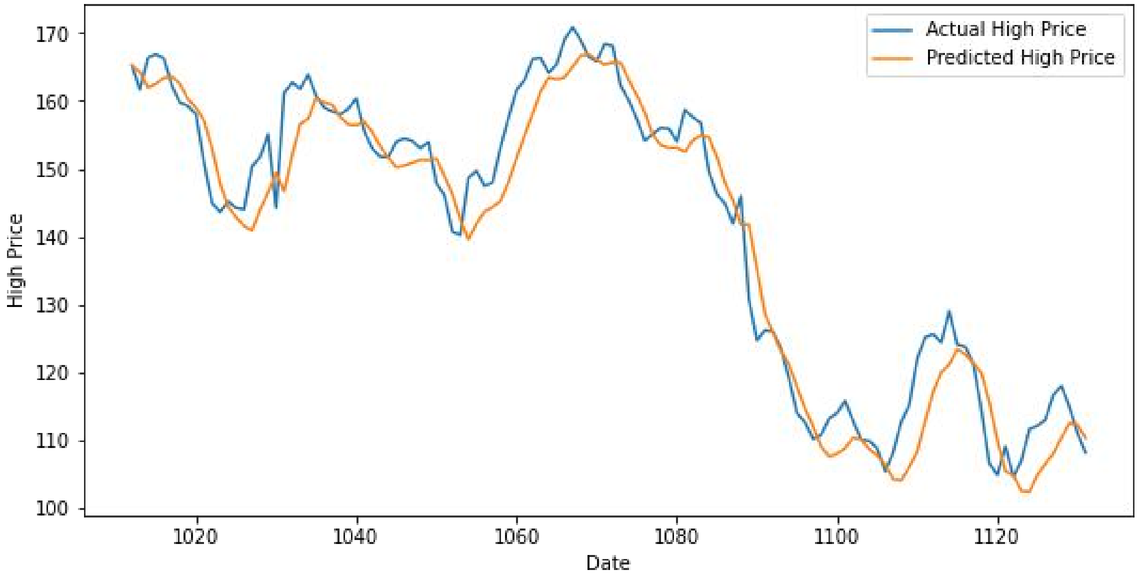

Figure 4.12: Test Plot

```
Train Score: 2.89 Mean Absolute Error
Valid Score: 2.77 Mean Absolute Error
Test Score: 4.23 Mean Absolute Error

Train Score: 3.59 Root Mean Squared Error
Valid Score: 3.66 Root Mean Squared Error
Test Score: 5.34 Root Mean Squared Error
```

Figure 4.13: Results Calculation of MAE and RMSE

In the figure 4.13, it describes the low error maintenance , every time the results of error is different because of the different starting conditions. In this research , I have focused on the results of the model rather than analyzing two different model performances. I am calling this proposed model is sustainable by analyzing its less error records. The actual price value and the predicted price values are pretty similar to each other that we can see in the total plot in figure 4.14. In table 4.1 , I have also shown the error calculation results according to the time parameter.

Times	MAE	RMSE
10	4.67	5.85
20	4.50	5.62
30	4.68	5.89
40	4.35	5.49
50	4.23	5.34

Table 4.1: Several Results of Test Score of MAE and RMSE According to Time Parameter

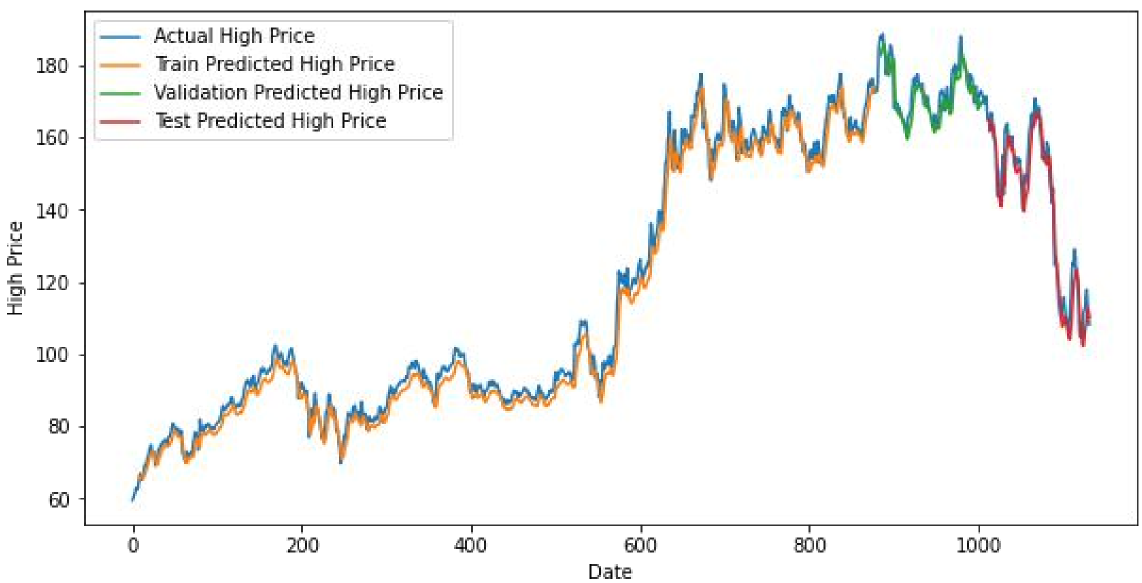

Figure 4.14: LSTM Performance of the Total plot

CHAPTER 5

FUTURE SCOPE AND CONCLUSION

5.1 Future Scope

The reign of stock market forecasting using deep learning is immensely grandiose and also goes far above the scope of a single research . Future work can entangle training with more data. More significant extent of what is presented here would be to train a similar model using data from multiple stocks and stock indices.Stock market is one of the most toughest unpredictable sector of finance and economy.A company can be effected depending on a large number of the stock price factors such as raw materials, suppliers, people's sentiment. In future works, I would like to concentrate more on the public reactions of a company to forecast the stock prices. In order to determine people's opinions about a company , reactions of people towards that can be analyzed and manipulated . It can be resolved from any social media or any well established companies. A hybrid model can include historical data which can be developed to predict stock prices more accurately. For analyzing and combining with sentimental data to predict the stock prices more accurately, other factors like environmental factors such as flood, storm etc. can be considered. In future studies to predict stock market activities, a distinction between neural networks and other types of models can be used, such as support vector machines and supervised models. Different models have already talked about various indices where variance and other variables vary and they behave separately. LSTM is a topic which can carry analysis and research work more deeply in future as there are very changing variable, moreover there are very bright future scope to create more accurate model for forecasting complex data variable depending on complex situation.

5.2 Conclusion

After a long research activity I can say I have succeeded the target which I have intent to represent that it is actually feasible for making logical predictions regarding stock price activity using Hybrid LSTM neural networks. Stock trading can be done with some decent ideas of stock market processing and also there is no lacking of sophisticated analytical tools for that purpose. In short, creating an actually profitable model was the intention of this research including exploring the forecasting capabilities of Neural Network which I have achieved. The use of LSTM in the forecasting section of stock market prices will be a continuing area of analytical research, as there are great future scope. The ultimate goal is to increase the investment and making sure that the LSTM approach get better representation of the forecasting future price, it also influence the time steps settings. This research proved that Hybrid LSTM model could forecast the future price with high accuracy and precision.

CHAPTER 6

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APPENDIX

Appendix : A Project Reflection

The intention of this appendix is to gleam my project. From Fall 2021 semester I have started my journey to make this analysis. My vision is making a different and unique type of LSTM model for forecasting stock price which will analyse data accurately , also there is motive to make this model long last than other models. There are a lot of struggles I faced while making this analysis as a beginner. The project "TIME SERIES ANALYSIS OF STOCK PRICE PREDICTION USING HYBRID DEEP LEARNING NEURAL NETWORK" will be very beneficial for Bangladesh stock market.This can be expected that people can easily analyse a company's stock history and can invest money without taking any risk. So, I presume that my project “TIME SERIES ANALYSIS OF STOCK PRICE PREDICTION USING HYBRID DEEP LEARNING NEURAL NETWORK” will be appreciated and accepted by all researchers and investors in the sector of stock market .

TIME SERIES ANALYSIS OF STOCK PRICE PREDICTION USING HYBRID DEEP LEARNING NEURAL NETWORK

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