A

Dissertation Report on

Cryptocurrency price prediction using machine Learning

Submitted

in partial fulfilment of the requirements for the degree of

Master of Technology

in

Electronics and Telecommunication Engineering

by

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K.E. Society's

Rajarambapu Institute of Technology, Rajaramnagar

(An Autonomous Institute, Affiliated to Shivaji University, Kolhapur)

2021-2022

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CERTIFICATE

This is to certify that, Miss Sabira Samad Mulla (Roll No-2023007) has successfully completed the dissertation work and submitted dissertation report on Cryptocurrency Price Prediction Using Machine Learning for the partial fulfillment of the requirement for the degree of Master of Technology in Electronics Engineering from the Department of the Department of Electronics and telecommunication, as per the rules and regulations of Rajarambapu Institute of Technology, Rajaramnagar, Dist: Sangli.

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DECLARATION

I declare that this report reflects my thoughts about the subject in my own words. I have sufficiently cited and referenced the original sources, referred or considered in this work. I have not misrepresented or fabricated or falsified any idea/data/fact/source in this my submission. I understand that any violation of the above will be cause for disciplinary action by the Institute.

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ACKNOWLEDGEMENTS

I must mention several individuals and organizations that were of enormous help in the development of this work. Professor S.R.Jagtap. my supervisor, philosopher and personality with a midas touch encouraged me to carry this work. His continuous invaluable knowledgably guidance throughout the course of this study helped me to complete the work up to this stage and hope will continue in further research.

I also very thankful to Dr. Mahesh S. Kumbhar HoP, and Dr Mahadev S. Patil HoD for their valuable suggestions, critical examination of work during the progress, I am indebted to them.

I also very grateful to Rajarambapu Institute Of Technology Rajaramnagar for his positive cooperation and immense kindly help during the period of work with him.

In addition, very energetic and competitive atmosphere of the electronics and telecommunication department had much to do with this work. I acknowledge with thanks to faculty, teaching and non-teaching staff of the department, Central library and Colleagues.

I sincerely thank to Dr, Sushma S. Kulkarni, Director for supporting me to do this work and I am very much obliged to her.

Last but not the least Mr. Samad Mulla my father, Mrs Anisa Mulla my mother, constantly supported me for this work in all aspects

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ABSTRACT

Crypto Currency is any form of digital currency that only exists digitally means online mode, this system has no central issuing or regulating authority but instead uses a decentralized model system, and this is used to record transactions and manage the issuance of new units, which relies on cryptography system to prevent counterfeiting and fraudulent transaction. Crypto currency is decentralized medium digital money that's based on blockchain technology. Now people are familiar with the most popular versions, Bitcoin and Ethereum, but there are more than 5,000 different crypto currencies in circulation. Bitcoin was established in 2009 and, for a lot of than two years, was the only blockchain based crypto currency's crypto currency is a standard medium of exchange that is digital currencies in encrypted and decentralized mode.As like US dollar, no central authority manages and maintains a crypto currency's value. Instead, these tasks are broadly distributed among cryptocurrency users via the internet. In addition to buying common goods and services, you can also invest in cryptocurrencies, just like you would in other assets. To create effective investments and trades, investment organisations, hedge funds, and even individual investors must study financial models to comprehend market behaviour. Investors typically make accurate forecasts by researching past cryptocurrency prices, corporate performance patterns, etc. Cryptocurrency unit values are completely random and unpredictable, according to the early phase of theories emerging from the guessing so here we are using LSTM algorithm for forecasting the upcoming one year value of bitcoin cryptocurrency and also finding the accuracy of algorithm.

Keywords: Cryptocurrency, Price Prediction, Bitcoin,Price Prediction.

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ABBREVIATIONS

LSTM	Long Short Term Memory
RNN	Recurrent Neural Network
GPU	Graphical Processing Unit
CNN	Convolutional Neural Network

Chapter 1

Introduction

1.1 Introduction

With the advance of technologies cryptocurrencies has lot of study possibilities. Due to its volatility and dynamism, predicting the value of a cryptocurrency can be challenging and time-consuming. Bitcoin and other cryptocurrencies are being utilised all around the world. Three different recurrent neural network (RNN) algorithm types are put forth in this study. Establish the prices for ethereum and three other cryptocurrencies. The projections made by the models are accurate to the mean absolute error. When using these techniques and models, gated perennial units (GRU) frequently outperformed long-remembering and Long Short Term Memory (LSTM) models for cryptocurrency forecasting. As a result, it is the formula that works the best. The Long Term Calculation forecast provided by GRU is the most accurate, with mape percentages for bitcon and etherium of 0.2454, 0.826, and 0.211, respectively (LTC). The Mean Absolute Percentage Error (MAPE) values for bitcoin, etherium, and other digital currencies are 5.990%, 6.85%, and 2.332%, respectively. Overall, the accurate costs of cryptocurrencies are near to the reliable results generated by the powerful prediction algorithms used in this study. These models are crucial because by assisting traders and investors in tracking down bitcoin trades and purchases, they will have a significant impact on the economy. In this study, we are making bitcoin price predictions. According to the most recent developments in value prediction technology, machine learning is compatible with the projection values now in use.

Value indices provide advice based on previous values. Additionally, machine learning makes use of a number of models to produce projections that are more reliable and understandable. Our main methods for value forecasting are regression and LSTM-based machine learning.

1.2 Technique

Bitcoin is a network-based, decentralised peer-to-peer cryptocurrency. It keeps anonymity while utilising encryption. Bitcoin is the digital currency that is used online the most. The vast majority of individuals are familiar with bitcoin due to its widespread use and open architecture. But the fluctuations in bitcoin's price are what have made it so well-known. Over the past 10 years, cryptocurrency has evolved into a crucial element of business initiatives and investment opportunities on the bitcoin market. The accurate and dependable assessment will help bitcoin investors choose the finest investments and open the door for potential future earnings development. However, because cryptocurrencies are so turbulent and complex, price prediction is difficult. Therefore, using a variety of machine learning techniques, researchers have looked at a number of factors that influence bitcoin's price as well as the patterns that underpin its volatility. The most powerful and well-known deep learning system is used to estimate the value of bitcoin. The real-time dataset includes aggregated information on the open, close, low, high, volume to, and price statistics for bitcoin as of the current date. The LSTM algorithm's primary objective is to accurately extract the bitcoin price. The results demonstrate how proficiently and effectively LSTM can resolve this issue.

1.2.1 Existing System

The highly mysterious and virtual money known as bitcoin is used by many investors. The invention of bitcoin is attributed to Satoshi Nakamoto. Bitcoin maintains a public record of each transaction that is made in the open since it is built on the blockchain. Scholars can use this to research the price fluctuations of bitcoin. It was initially challenging to accurately depict and anticipate values due to a lack of tools and techniques as well as a need for more data. In terms of technology, though. As technology improved, researchers' interest in developing models that might describe how to calculate monetary values increased. Deep learning and machine learning jobs became more prevalent as a result. A review of the literature, which included several well-known publications on the relevant topic, yielded impressive findings [8].

1.2.2 Analysis

An encrypted type of virtual cash is known as a cryptocurrency. These are built utilising a decentralised network design based on the blockchain. Cryptocurrencies operate in a different manner from typical online transactions. The absence of a single, central ledger utilised by cryptocurrencies sets them apart from ordinary digital transactions in important ways. Instead, all users of the system record transactions concurrently, reducing the likelihood of a systematic attack. This provides an important clarification regarding the security and hackability of cryptocurrency. Compared to other virtual currencies, the currencies are built on a safer interface.

1.2.3 Preprocessing

We look into how predictable the bitcoin market is for forecast timeframes ranging from one to sixty minutes. For the aforementioned prediction tasks, all machine learning models outperform a random classifier, although gradient boosting classifiers and recurrent neural networks have been proven to be more effective. Only a fraction of the technological, blockchain-based, sentiment interest-based, and asset-based components of our activities are now available. After then, a few capabilities based on blockchain and emotion are introduced, but the technical underpinning of the majority of approaches is still crucial. We also find that predictability increases as prediction bounds are widened. For instance, a quantile-based long-short trading strategy may generate monthly returns of up to 39% before transaction costs; however, once transaction costs are taken into account, the relatively brief holding periods result in losses.

1.3 Goals and Purpose

Aim

The goal is to develop a system that can forecast and assess the worth of cryptocurrencies for the following year and show the user the analysis chart.

Objectives

The planned work has the following objectives:

- To review the current literature to understand the existing methods.
- To analyze the existing methods for finding crypto currency prediction with the Current Date.
- To collect and train the data.
- To develop new algorithms for price prediction and find the best result.
- To test the accuracy of the developed algorithm using confusion Matrix.
- To verify the results.

1.4 Layout of the thesis

The project's broad introduction and the goals and objectives of the study are both found in Chapter 1. A summary of the literature pertinent to the current endeavour and the theories supporting the suggested system are both included in Chapter 2 of the book. In Chapter 3, the project's intended work is described in depth along with a block diagram and a simulation. The system's findings and discussions are presented in Chapter 4. The results of the dissertation are presented in Chapter 5 of this work.

1.5 Closure

This section demonstrates the importance of bitcoin price prediction. As discussed in the appropriate chapter, various methodologies are used to forecast cryptocurrency. The methodologies necessary for deep neural network-based bitcoin price prediction are covered in Chapter 2. Simply put, everything has been evaluated, and the future development of it has been completed.

Chapter 2

Literature Review

2.1 Introduction

A literature review is an essential part of every project. It helps to narrow the scope of our inquiry. Information on cited research papers and audit papers can be found in this section. There are citations for numerous scientific articles, including journal papers.

2.2 Literature Review

The application of machine learning by computer algorithms to predict longer-term events using prior data (ML). Many of the benefits of ML-based models, including as increased accuracy and delivering forecasts that are almost or exactly the same as the actual outcomes, are not available from alternative forecasting methodologies. Examples of machine learning include neural networks, deep learning, and support vector machines. The efficacy of a portfolio is allegedly increased by bitcoin in two separate ways. The first goal is to lower quality deviation, followed by raising investor allocation. An acceptable cryptocurrency allocation could range between five and twenty, depending on the investor's risk tolerance. Using two machine learning techniques, random forests (RF) and random gradient boosting machines, the authors forecast statistics (SGBMs)[1]. This programme using artificial intelligence can forecast bitcoin prices. For the risk-related investment plan, the right decision is made at the right time. This study offers a hybrid cryptocurrency prediction method and focuses on litecoin and monero. The authors use three-hour time intervals of minute-sampled bitcoin returns to add RV data. A number of machine learning techniques, including ANN (MLP, GRU, and LSTM), SVM, and ridge regression, were evaluated using the heterogeneous autoregressive completed volatility (HARRV) model with the optimal lag settings. The suggested strategy, which establishes individual coin pricing, is applicable to various cryptocurrencies. To forecast bitcoin values, the authors use support vector machines and regression toward the mean. The daily closing data is used to develop the forecasting models for Bitcoin prices. For multivariate research based on closely related traits, we integrated multivariate analysis with deep learning methods such as conjugate gradients and linear searches. if it is even possible to predict the price of bitcoin [3]. We investigate the price changes of Bitcoin, Ethereum, and Ripple. An extended STM (LSTM) everlasting neural network is connected to an artificial neural network (ANN). They found that ANNs have a greater reliance on previous data. The short-term dynamics of the LSTM make it more efficient in retrieving information from the past. [4]. Both linear discriminant analysis and logistic regression were able to predict the daily value of Bitcoin with a 66 percent accuracy rate using high-dimensional data. With accuracy rates of 66% and 65.3%, respectively, the Surpassing approach (a related machine learning technique) exceeds the benchmark results for daily worth prediction [5]. Deep learning algorithms might be useful for identifying patterns in bitcoin price movements in larger datasets. Evidence suggests that LSTM, as opposed to MLP, is more accurate and trustworthy over the long term. In this case, the MLP and LSTM models are applied to the Daily, Hourly, and Minute data. The findings demonstrate that neural networks are better able to make accurate predictions when there is less variation between two successful pricing values. The outcomes show that the LSTM performed somewhat, but not considerably, better than the MLP [6]. Modern deep learning models like LSTM, BiL-STM, and convolutional layers are used in the recommended ensemble models as component learners. The effectiveness of ensemble approaches for averaging, bagging, and stacking under both classification and regression settings was assessed as part of a comprehensive experimental study[7]. By anticipating the exchange rate of digital coins, cryptocurrency dealers and bitcoin brokers can gain a competitive advantage. The trained model can be used because the procedure produces accurate results. XG-Boost outperforms earlier algorithms in daily records of the exchange values of digital coins, especially Litecoin, Monero, and Ether. The RMSE, MAPE, and MAE were used to evaluate the effectiveness of the prediction model[8].

2.3 Closure

This section provides an overview of the literature review, papers, and evaluation procedure. The third section closes with a discussion of the proposed project and task execution.

Chapter 3

Proposed Work

3.1 Introduction

This chapter will go over the strategy used to achieve the project's goals, with a focus on how it was implemented. Analyzing each step will be critical to completing this assignment. Every decision made and consequence of the approach utilised will be questioned until the project is completed. This project makes use of the Python programming language, the Streamlit web framework, and the Anaconda navigator. The LSTM, or linear regression, technique is used to forecast bitcoin prices.

3.2 Developed Block Diagram

Figure 3.1 depicts the suggested system's architecture. The datasets utilised This sample was identified using data from Yahoo Finance, and the information obtained will be used to perform feature extraction. Only associated volume, near, low, higher prices, and market values are taken into consideration when we extract attributes. If the accuracy of any data set's values can be verified, they are replaced with a description of the relevant characteristic. In accordance with the length of time, all data sets are combined into one. If we look at the trend in the price of Bitcoin in 2022, the neural network will have this information. Data will next be assessed and trained using the LSTM model to produce trained data. To get a forecast value, we will project the values. Finally, training data will be used to forecast cryptocurrency values. We are obtaining the data for the suggested design from Yahoo Finance. It is initially necessary to load and train the dataset.

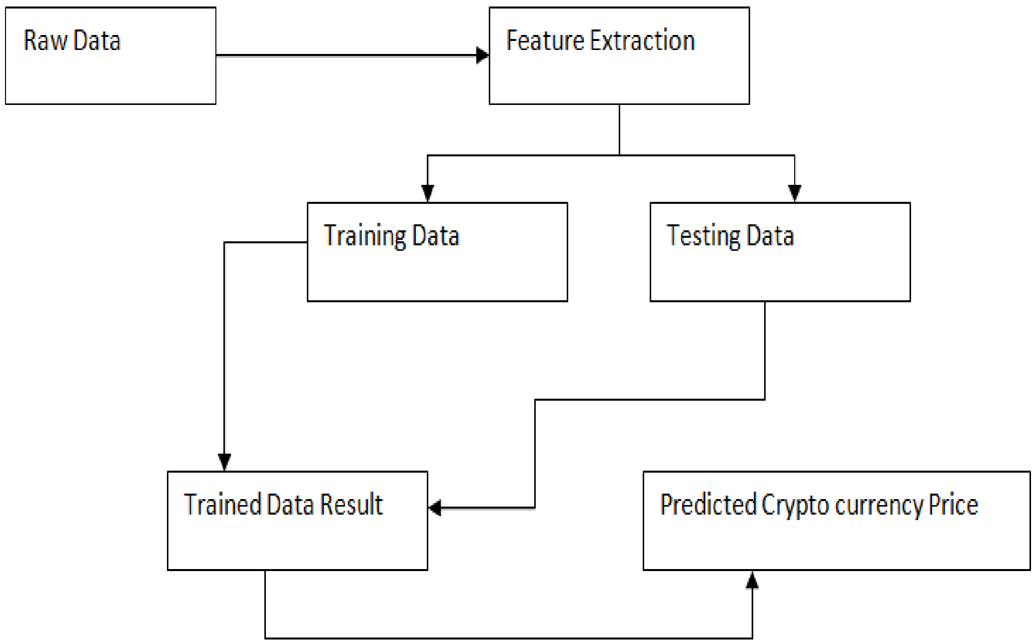


Figure 3.1: Block Diagram of the system

After training the dataset, testing will be done in which we will predict prices for future dates not covered by the trained dataset.

Dataset: - Yahoo Finance. (https://www.kaggle.com/achintyatripathi/ eda-autoviz-class-one-line-code-yahoo-stock-price?scriptVersionId=42446951)

3.3 Flow Chart of the System

Figure 3.2 displays the flowchart for the suggested system. This approach involves training the system on data before putting it to the test. This system makes use of the calculation for recall, accuracy, precision, and support. The analysis is done through the confusion matrix. The confusion matrix first displays the LSTM model's support, accuracy, and precision.

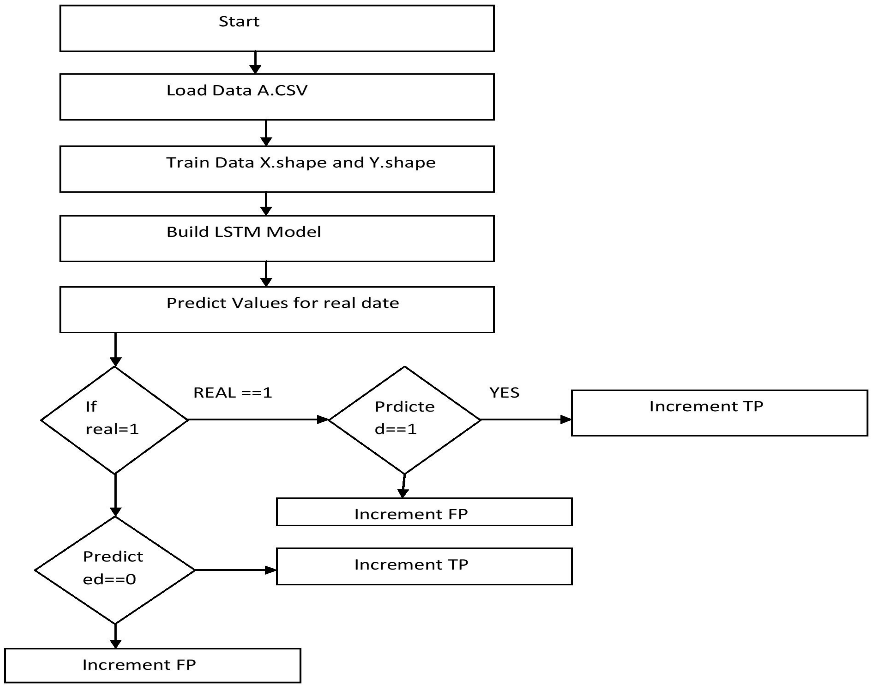


Figure 3.2: Flow Chart of the Proposed System

3.4 Algorithm Used

3.4.1 LSTM Algorithm

Because they have the ability to recall previous data, LSTMs are useful for solving problems involving sequence prediction. This is important since the price of a bitcoin might change over time. LSTM networks can enhance memory retention for previously learnt information by altering current neural networks. The speech recognition and machine translation businesses, among others, rely on this behaviour to address complex problems. However, LSTMs present a challenge for deep learning. Understanding LSTMs and how concepts like bidirectional and sequence to sequence apply to the field could be difficult. However, when discussing the capabilities and operations of LSTMs, those who created them are among the most knowledgeable.

The Internal Structure Of LSTM

Using particular gates, each LSTM layer can access information from both the layer above it and the one below it. The data is processed by the LSTM cells, various gates (such as the forget gate, input gate, etc.), and numerous operations.

The main advantage is that it makes it possible to temporarily store patterns in each LSTM cell. It should be stressed that the LSTM can remember significant information while forgetting useless information.

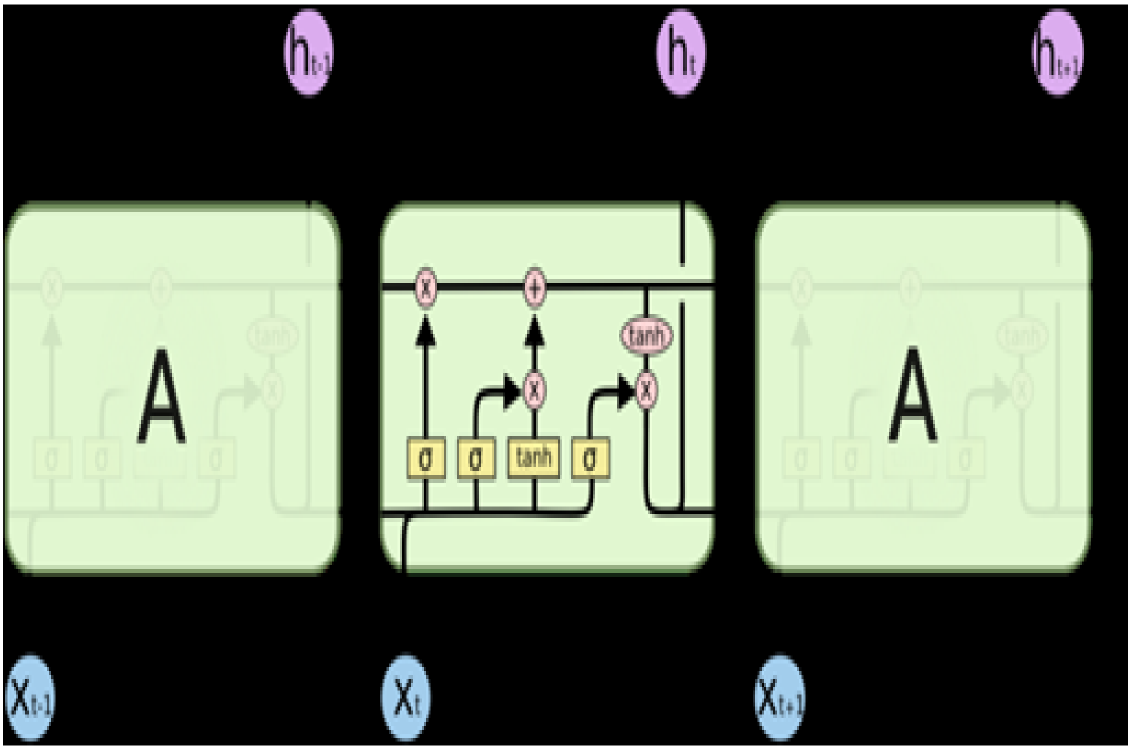


Figure 3.3: LSTM Architecture

Figure 3.3 demonstrates how the LSTM design uses the concepts of gates, short-term memory (STM), and both long-term memory (LTM) and short-term memory (STM). A neural network activation function called Tanh Activation has the expression f (x) = e x e x e x + e x. Due to its better fit for multi-layer neural networks, tanh function has historically enjoyed greater popularity than sigmoid function. Previously, the inputs were hidden (ht-1). To swiftly and easily execute computations using both Long Term Memory (LTM) and Short Term Memory, LSTMs leverage the concept of gates (STM).

Forget Gate: As it passes through the forget gate, the LTM eliminates extraneous data.

Learn Gate: We may apply the critical knowledge we most recently learned via STM to the current input thanks to the relationship between the event (current input) and STM.

Recall Gate: An updated LTM is created at the remember gate by combining the

LTM data that we didn't forget, the STM data, and the event data.
Use Gate: To make an updated forecast of how an event will turn out.This Gate additionally uses LTM, STM, and Event in addition to STM.

LSTM Network

Any neural network with a bidirectional long-short term memory (BI-LSTM) is capable of keeping track of sequence data that moves both forward (from the future to the past) and backward (from the present to the past) (past to end). A bidirectional LSTM accepts input from both ways, in contrast to a typical LSTM. We can only make input flow one direction, either backwards or forwards, using the traditional LSTM. However, with bi-directional, we can take into account feedback from both directions, protecting the present and the future.

```
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 bidirectional (Bidirectiona  (None, 49, 98)           21952
 l)

 dropout (Dropout)           (None, 49, 98)            0

 bidirectional_1 (Bidirectio  (None, 49, 196)          154448
 nal)

 dropout_1 (Dropout)         (None, 49, 196)           0

 bidirectional_2 (Bidirectio  (None, 98)               96432
 nal)

 activation (Activation)     (None, 98)                0

=================================================================
Total params: 272,832
Trainable params: 272,832
Non-trainable params: 0
```

Figure 3.4: LSTM Network

Figure 3.4 depicts the LSTM Network with layer and output form. The outcomes show the outputs and settings for each tier. Details such as total, trainable, and non-trainable characteristics are included in the evaluation section.
Cell nation (ct) - The internal memory of a mobile device, which contains both recent and distant memories, is referred to as Cell Nation (ct).
Hidden nation (ht) - The current input, prior hidden nation, and molecular input were used to determine the output nation data, also known as the hidden nation

(ht). Finally, you'll use it to predict how the price of bitcoin will fluctuate in the future. For instance, the hidden nation may further select to just recover the short-term or long-term memories, or even each type of memory, stored inside the molecular nation in order to make the upcoming forecast.

Input gate (it) -The input gate controls how much recent entries' data is provided to the molecular country (it).

Forget gate (ft) - How much knowledge from the past and present molecular countries will be integrated into the current molecular country is determined by the forget gate (ft).

Output gate (ot) - The output gate (ot), which gauges the quantity of data from the modern mobile nation that enters the hidden nation, enables LSTM to distinguish between long-term and short-term memories as necessary.

3.5 LSTM Architecture

People are more likely to remember what was in a photo if you question them about it again two minutes later. The specifics may have been forgotten or only partially erased if they inquire about the same perspective a few days later. The first case requires the use of recurrent neural networks (RNNs). LSTMs are required in the second scenario due of the very huge memory capacity. These are known as "long-term short memories".

- **Forgetting Mechanism:**The scene's unnecessary features should be forgotten, according to the forgetting mechanism.
- **Saving Mechanism:** Keeping significant data that will be useful in the future is a saving mechanism.
- **The architecture of LSTM:** LSTMs use the idea of a gate to efficiently perform calculations utilising both Long Term Memory (LTM) and Short Term Memory (STM).
- **Forget Gate:** Every unneeded piece of data is deleted when LTM passes through the forget gate.
- **Learn Gate:** We can apply the most recent STM information necessary to the current input by integrating the event (current input) and STM.

- **Remember Gate:** The link between the event (current information) and STM allows us to apply current STM knowledge to the current passed input.
- **Use Gate:** This gate forecasts the outcome of the current event using an updated STM, LTM, and event.

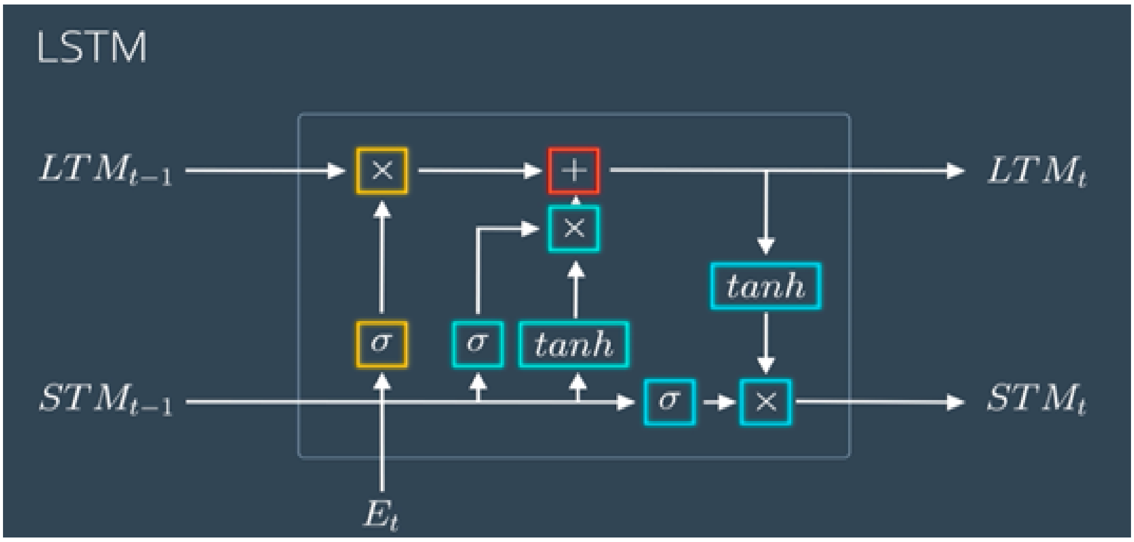


Figure 3.5: LSTM Network Flow

The LSTM architecture is depicted in Figure 3.5 with the following details. Typically, RNNs are networks made up of sigma cells and tanh cells, two types of common recurrent cells.

- **Learn Gate:** Only relevant data is used as input for prediction from the event and previous short-term memory. Training LSTMs resolves the Vanishing Gradient problem (too-small weights under-fit the model), but it still has to address the Exploding Gradient problem (weights become too large that over-fits the model). Python frameworks like TensorFlow, PyTorch, Theano, etc. make it easy to train LSTMs. To train deeper LSTM networks, however, a GPU is necessary, much as it is for RNN training. Since they take care of the long-term dependencies, LSTMs are commonly used in tasks like language production, voice recognition, picture OCR models, etc. Additionally, object detection has picked up on this technique (mainly scene text detection). Figure 3.6 depicts the learning gate in visual form. As seen in the diagram, the learning gate is where the short-term memory is stored.

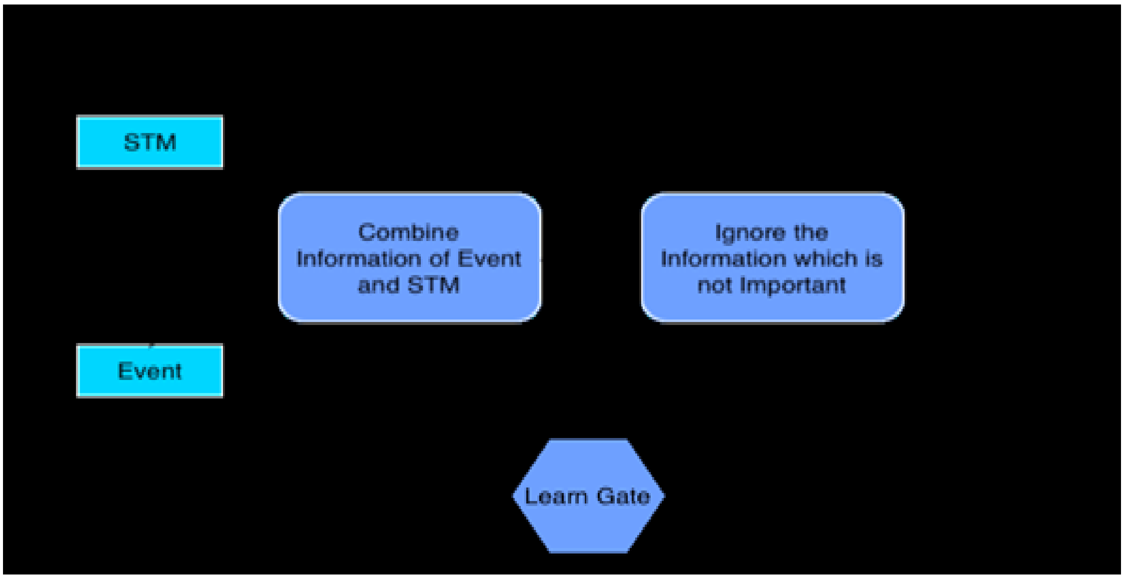


Figure 3.6: Learn Gate

Figure 3.6 shows the learning gate.

- **The Forget Gate:**Uses knowledge from the previous long-term memory to make a distinction between knowledge that should be forgotten and knowledge that should be lost (LTMt-1). The forget gate is the first representational architectural element of the LSTM architecture (ft). The sigmoid activation function receives data from the previous hidden state (Xt) and the current input (Xt) (ht). Keep the output value if it is closer to 1, and throw it away if it is closer to 0. The forget gate is used to delete data that is no longer required for the cell state. Weight matrices are applied to the gate's two inputs, xt (the input being used right now) and ht1 before bias injection (the output from the cell before it). The activation function generates a binary value for the result. If a cell's output is 0, a piece of information is lost, but if it is 1, it is saved and can be exploited. The data is retained for future use.

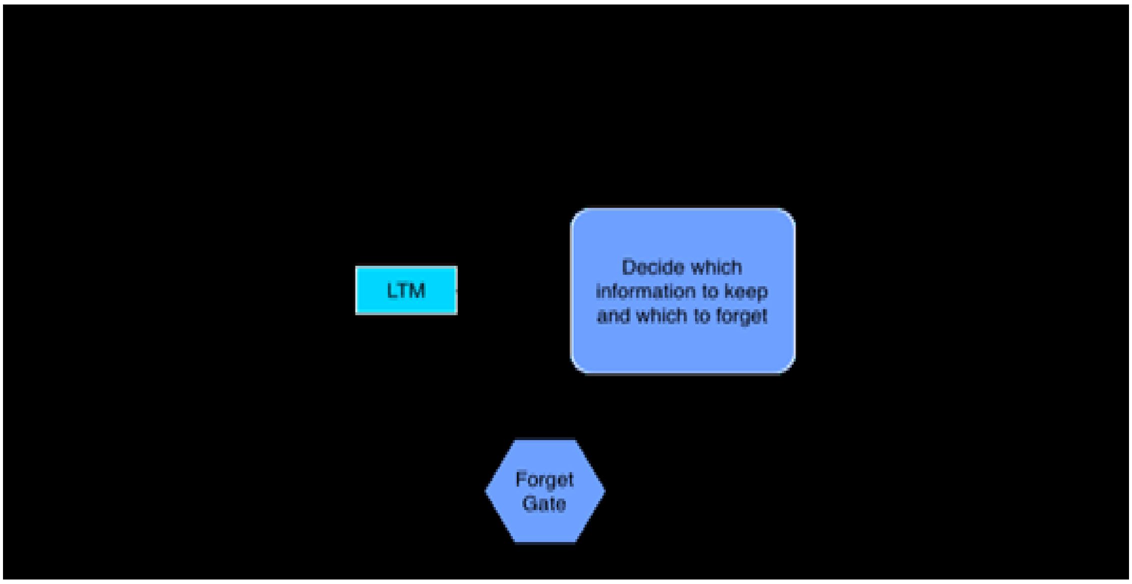


Figure 3.7: Forget Gate

The forget gate and long term memory are shown together in Figure 3.7. It chooses which data to keep and which to discard.

- **The Remember Gate:** Produce output by fusing current events with short-term memory (STMt-1) (Et).

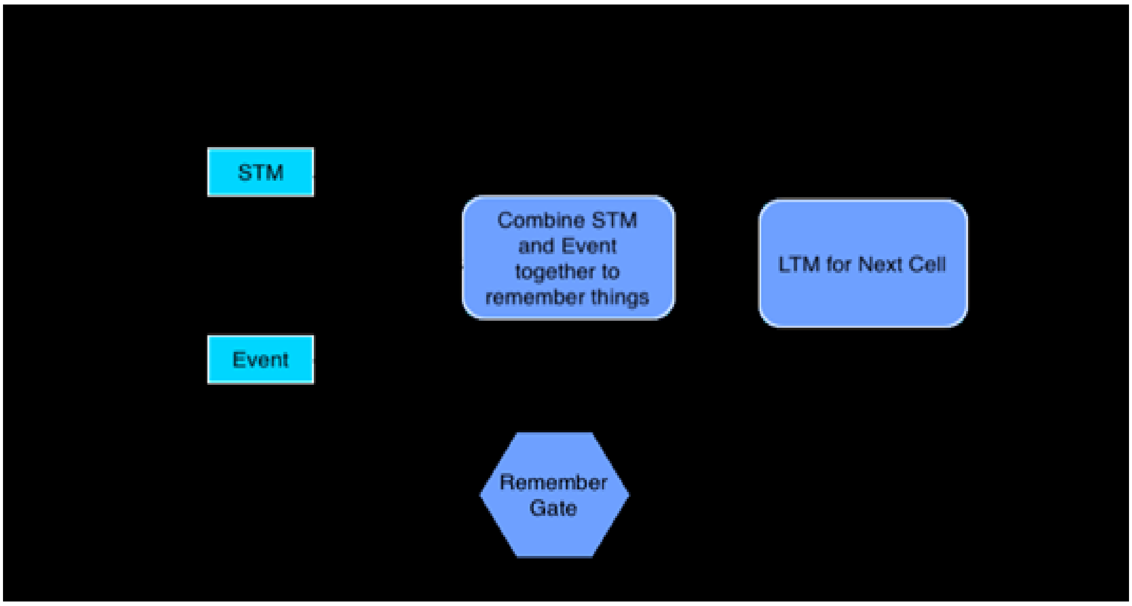


Figure 3.8: Remember Gate

The Remember Gate with long-term and short-term memory is shown in Figure 3.8.

- **The Use Gate:** The STM for the subsequent cell is created by combining the output from the preceding cell's Long Term Memory and Short Term Memory.

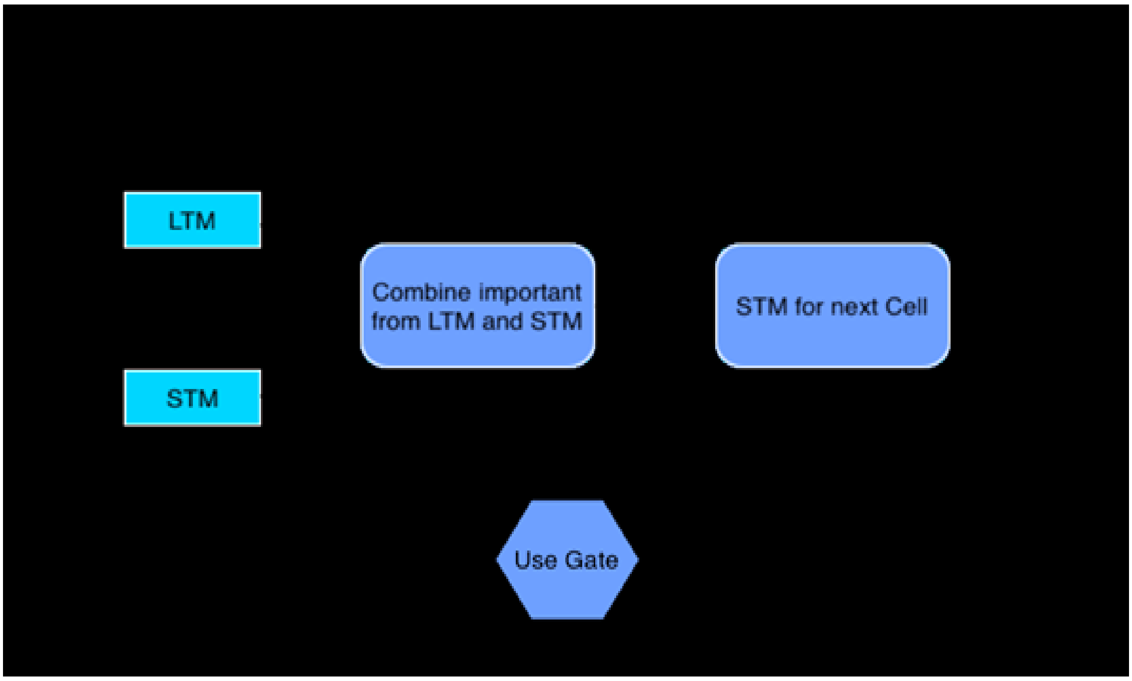


Figure 3.9: Use Gate

The usage gate merging significant data about the data is shown in figure 3.9.

- Training data for LSTM :- 90 %
- LSTM test results:- 10 %
- Financial datasets are among the web sources from which the data for LSTM is derived. Before testing it and providing value predictions, will train the dataset.

3.5.1 How LSTM Process Data

- **Import the data :** Data for both the test and the train are downloaded from the internet. The open price will be used to produce forecasts.
- **Feature Scaling :**You download the practice and test data from the internet. We'll make predictions based on the open price.
- **Data Structure Creation :** making a data window that slides
- **Data Reshaping :** We make projections using open pricing. We just have one distinct sign or trait. Using the same data processing techniques, we

can add further indications. To do that, a new dimension for the number of hands must be introduced.

- **Model Building:** :LSTM is being used to create a NN regressor for continuous value prediction. Set up the model first.
- **Model Compiling**
- **Model Fitting**
- **Data Preprocessing for test dataset**
- **Model Prediction**
- **Result Visualization**

3.5.2 Drop Out Function:

- When a network is being trained, a regularisation technique called dropout probabilistically removes input and repeat connections to LSTM units from activation and weight updates. In turn, overfitting is reduced and model performance is improved. As a result, there is less overfitting and model performance is enhanced.

3.5.3 Dense Layer:

- In a dense neural network with many connections, that layer is the norm and the one that is used the most. The dense layer processes the input using the next step to create the output.
- output = activation(dot(input, kernel) + bias) where
- The data's origin is input.
- Weight data is represented by a kernel.
- Dot refers to the corresponding weights for each input's NumPy dot product.
- Machine learning uses bias, a distorted value, to improve the model.
- Activation is a metaphor for the activation function.

3.5.4 LSTM Works in 3 Step Process

- Step 1: Determine how much previous information you should be able to remember. The decision of which data to reject comes first in the LSTM process. emanating from the cell at that specific moment. To ascertain this, the sigmoid function is employed. When computing the function, the past state and the current input xt are both taken into account (ht-1).
- Step 2: Consider the impact of this component on the current situation. Two parts make up the second layer. The tanh function and the sigmoid function are the two. It chooses the values of the sigmoid function that will be communicated (0 or 1). The tanh function weighs the significance to determine its importance (-1 to 1).
- Step 3: How much of the present cell state will be created is up to you. The final step is choosing the result. In order to determine which components of the cell state are output, we first run a sigmoid layer. We multiply the cell state by the output of the sigmoid gate after a tanh check to make sure the values are between -1 and 1.

3.5.5 Input/Output LSTM

- import numpy as np
- from keras.models import Sequential
- from keras.layers import Dense
- from keras.layers import LSTM,Dropout
- from sklearn import metrics
- From this we can import the libraries
- data = [[100,101,102,103,104,105,106,107,108,109]]
- data = np.array(data, dtype=int)
- target = [[100,101,102,103,104,105,106,107,108,109]]
- target = np.array(target, dtype=int)
- print('me')

- print(data)
- print(target)
- data = data.reshape((1, 1, 10))
- target = target.reshape((1, 1, 10))
- print(data)
- print(target)
- model = Sequential()
- model.add(LSTM(10, input_shape=(1, 10),return_sequences=True))
- model.add(Dense(10))
- model.add(Dropout(0.2))
- model.add(Dropout(0.2))
- model.add(Dense(10))
- model.compile(loss='mean_absolute_error', optimizer='adam',metrics=['accuracy'])
- model.fit(data, target, epochs=1, batch_size=10)
- print(model.summary())
- predict = model.predict(data)
- print(max(predict*10))

3.6 Logistic Regression

Using a predetermined set of independent variables, it predicts the category dependent variable. Using logistic regression, the result for a categorical dependent variable is predicted. As a result, the result must be an absolute or discrete value. Instead of providing exact values between 0 and 1, it gives probabilistic saves in that range. Only two outcomes are possible: true or false, 0 or 1, yes or no. With one exception, the operations of logistic regression and linear regression are comparable. Regression, as opposed to logistic regression, is used to address classification challenges. By utilising linear regression, the issues are addressed.

As a result, we propose a "S"-shaped logistic function that anticipates two maximum values as an alternative to fitting a regression line in logistic regression (0 or 1). A wide range of potential outcomes are represented by the logistic function's curve, including whether or not the cells are malignant, whether or not a mouse is overweight depending on its weight, etc. Because it can classify new data using both continuous and discrete datasets, logistic regression is an essential machine-learning technique. The parameters that accurately categorise observations from a variety of data sources can be discovered using logistic regression. The logistic function is demonstrated in the illustration below:

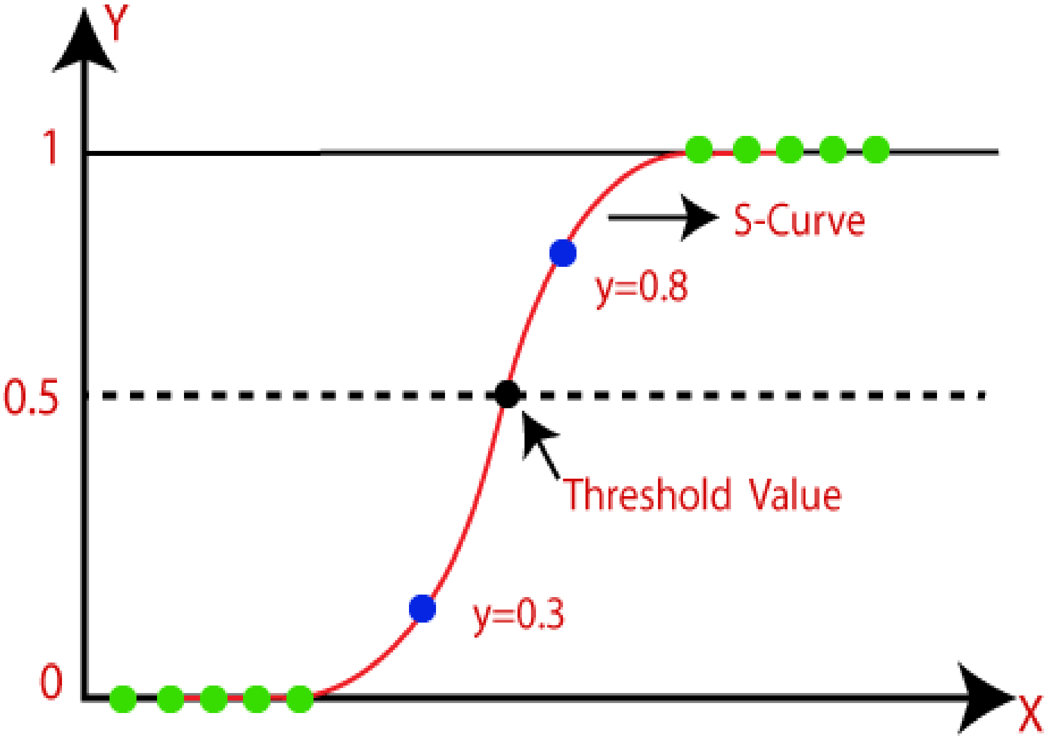


Figure 3.10: Logistic Regression

Logistic Function (Sigmoid Function):

The sigmoid function, a mathematical technique, is used to convert the projected values to probabilities. Any real number between 0 and 1 that it changes into a different material. Given that the outcome must fall between 0 and 1, the logistic regression assumes a "S" curve shape. The S-form curve is also known as the logistic function and the sigmoid function. In logistic regression, the threshold value concept is used to determine if a probability is 0 or 1. For instance, there are typically just two possible values for whether a number is above or below a threshold: 1 or 0.

Types of Logistic Regression

Logistic regression can take many different shapes, depending on the categorization it does. In light of this, there are three forms of logistic regression. Let's talk about each of them separately.

- Binary Logistic Regression
- Multinomial Logistic Regression
- Ordinal Logistic Regression

Binary Logistic Regression

The most widely used kind of binary logistic regression. It falls within the just-outlined subcategory of logistic regression. One of two formats, such as 0 or 1, can be used for the dependent target variable of this kind. Examples include cancerous or not, successful or not, admitted or not admitted, etc.

Multinomial Logistic Regression

Multinomial logistic regression is used when the target or independent variable has three or more possible values. Based on the characteristics of the chest X-ray images, you can choose one of the three possibilities (no disease,COVID- 19). The multinomial logistic regression employing the attributes will divide the example into one of the three outcomes in this case. Of course, the target variable may have more than three possible values.

Ordinal Logistic Regression

Normal logistic regression is utilised when the target variable has an ordinal nature. With this approach, each category is given a number, and they are organised logically. The target variable contains more than two categories as well. For instance, exam grades are classified and scored using numerical criteria. You could use fundamental A, B, or C-level steps.

3.7 Random Forest Algorithm

Favourite machine learning algorithm Random forest is a part of the supervised learning strategy. It might be used to solve regression and classification ML issues. Its core is machine learning, which brings together a variety of classifiers to solve complex problems and enhance model performance. The category of unauthorised repositories includes a variety of tree determination kinds. A considerable sum of money is needed to complete the anticipated work of gathering data from various data sources. The more trees there are, the better and harder it is to manage the tree sector. A few up-to-date information collections have to be made available so that courses might forecast actual consequences as opposed to only predicted one. There should only be a few fundamental assumptions in each tree. This model is simpler to set up when compared to other ones. The major arrangements that have been made and that, in whatever capacity, have functioned superbly foretell efficacy and reality. That may be accurate given the absence of compelling proof. The suggested assignment makes use of Python 3.6.4, sci-kit-learn, Panda, Matplotlib, and other crucial libraries. We erased the information from bitinformatics.com using the control key. Data that has been removed now contains new data. The percentage of the brochure that is regarded to be exam-related is just 20%, while the remaining 80% is thought to be curriculum-related. Intelligent calculations have been used to predict retreats and timberlands. Excellent investigation The pre-handling line is the target of the attack, and the cost is determined by the grades assigned to the id.

Why we use Random Forest Algorithm

- In comparison to other algorithms, it takes less time to train.
- Even with a massive dataset, it functions effectively and generates rather accurate predictions.
- Even though a sizable amount of the data is missing, accuracy can still be kept.

Root Mean Error Square(RMSE)

Early error frequently uses the contrast between the evaluated value of a particular example or worth and population or test values. A fraction of the producing error is made up by the RMSE.

$$RMSE = \sqrt{\frac{1}{n}\Sigma_{i=1}^{n}\Big(\frac{d_i - f_i}{\sigma_i}\Big)^2} \tag{3.1}$$

- Data from a financial dataset is used as the source of test and train values for Random Forest.
- Therefore, fi is the calculated result after using random forest.

- oi is the train dataset's actual value.
- The loss function we can square root of is called RMSE.
  Example of RMSE
- fi=103 – Predicted Value from test Dataset
- oi=102– Actual Value from train dataset
- cal=(103-102)=(1)*2=1
- Cal =Squre root(1)=1

3.8 Confusion Matrix

A confusion matrix contrasts actual and expected values in figure 3.11. It has a table-like appearance and evaluates the effectiveness of our machine-learning categorization algorithms.

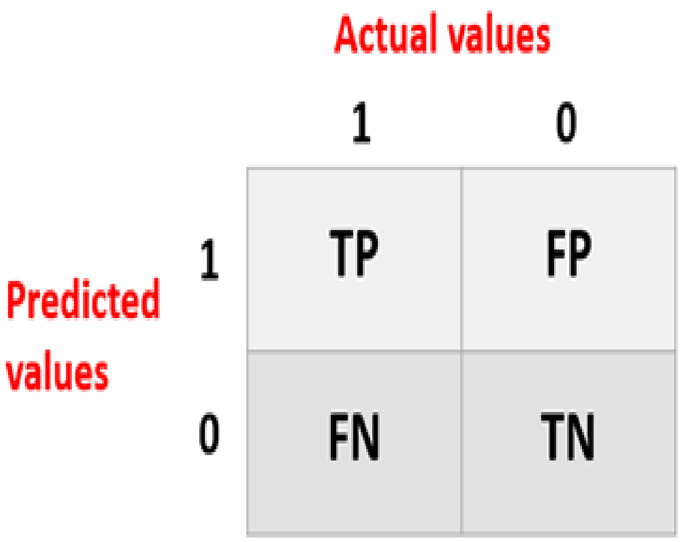


Figure 3.11: Architecture of Confusion Matrix

3.8.1 Elements of Confusion Matrix

Values that both performed well and were anticipated to be positive are said to be true positives (TP). False positives, or FPs, are values that were anticipated to be negative but ended up being positive. Type I Error is another name for it. It is known which predicted negative numbers ended up being positive. False negatives, often known as FNs, are a sort of error similar to Type II. True negative values are those that were accurately and genuinely projected to be negative.

3.8.2 Logic behind Confusion Matrix

When the outcome includes two or more classes, a machine learning classification system's effectiveness is assessed. The table displays four separate sets of projected and actual data. The true logic of confusion matrix, together with expected and actual values, are displayed in Figure 3.12.

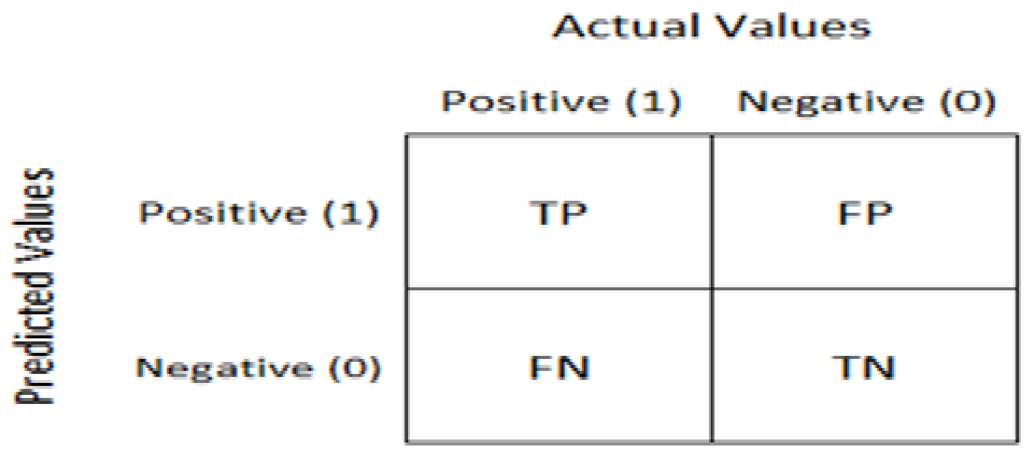


Figure 3.12: Logic of Confusion Matrix

3.8.3 Architecture of Confusion Matrix

By offering a tabular display of the various results of the prediction and discoveries, a confusion matrix aids in the visualization of the effects of a categorization exercise. It makes a table containing all of the predicted and actual values from the classifier. The following diagram illustrates the confusion matrix's fundamental structure. the proportion of times that favorable findings really match those expected to be positive. As you properly expected, the value is positive. The percentage of times our model predicts negative values as positives in error (or vice versa). Despite what you had believed, the worth is higher than you had anticipated. The percentage of times our actual negative values agree with anticipated negative values is known as the true negative. Your prediction of a negative value was accurate, and that is what the result is. The Architecture of Confusion Matrix is displayed in Figure 3.13.

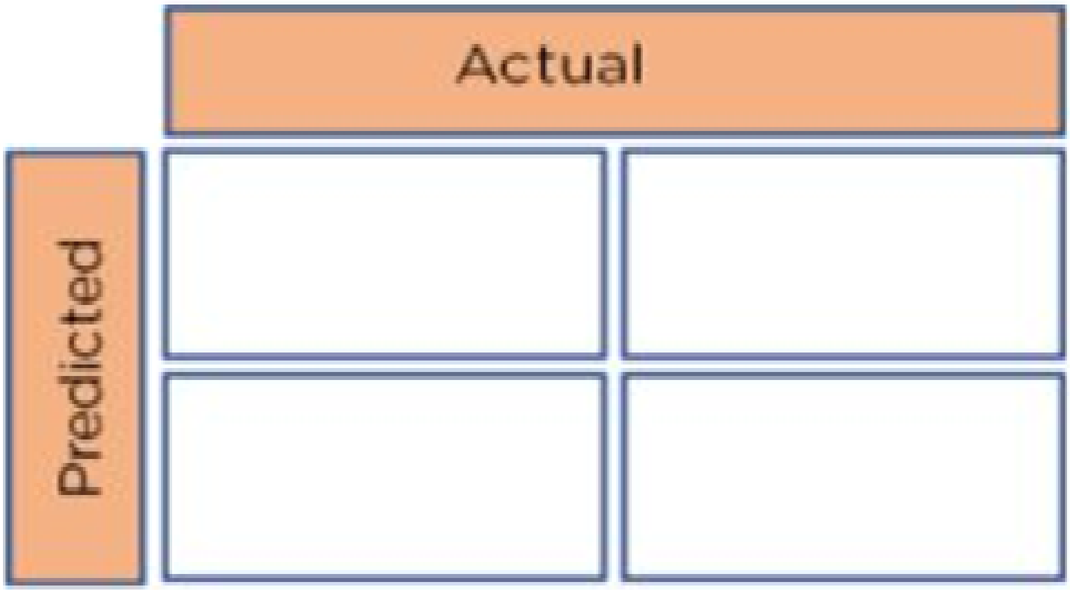


Figure 3.13: Confusion Matrix Data

- **True Positive:** Interpretation: Your favourable prediction came true
- **True Negative:** Interpretation: As you had predicted, the outcome was negative.
- **Untrue Positive (Type 1 Error):** Although your forecast was accurate, it was a good one.
- **Erroneous negative (Type 2 Error) Interpretation** You were mistaken in thinking the outcome would be bad.

A binary classification problem's confusion matrix looks like this.
Precision: It can be explained by the number of accurate outputs generated by the model or by the proportion of accurately predicted positive classifications that actually occurred. You could determine it by using the formula below.

$$Precision = TP/(TP + FP) \tag{3.2}$$

Recall: The percentage of positive classifications that our model correctly predicted is shown by this statistic. There has to be a big recall.

$$Recall = TP/(TP + FN) \tag{3.3}$$

3.9 Closure

This section describes the proposed system and its architecture related information.

Chapter 4

Results

4.1 Introduction

The experimental findings for the built-in system are presented in this chapter. This displays the output design, libraries, and software specification for the created system.

4.1.1 Python

Python is an interpretative, object oriented programming language. Included are classes, modules, exceptions, dynamic typing, and highly high level dynamic data types. In addition to object oriented programming, it also supports a number of other programming paradigms, such as procedural and functional programming. Python is quite versatile and has a straightforward syntax. It includes interfaces for various system calls, libraries, and window systems and can be modified in C or C++. It can also be applied to programmes that need programmable user interfaces as an extension language. Linux, Macos, and Windows are just a few of the unix platforms that python can run on. Programmers don't always have to start from scratch because the python library provides essential building blocks. You can access, manipulate, and transform your data with the help of python libraries, which is essential for machine learning. These are some of the most complete AI and machine learning libraries that are currently available.
Scikit-learn to administer basic ML methods like classification, regression, logistic and linear regression, and clustering.
Pandas are utilised in the analysis of complex structures and data. You can mix,

filter, and compile data from various outside sources using it (such as excel).
Keras for deep learning, is used. It employs the GPU in addition to the CPU of the computer, enabling quick calculations and prototyping.
TensorFlow Uses extensive data sets to build, train, and apply artificial neural networks, which are used to manipulate profound understanding.

Platform independence python is versatile, easy to learn, and easy to utilise. It shows that python, which is required to construct machine learning, can be used on all platforms, including windows, linux, unix, macos, and 21 more. To convert the process from one platform to another, developers make a few minor modifications and alter a few lines of code to produce executable code for the selected platform. Using software tools like pyinstaller, developers can prepare programmes to run on a variety of platforms. This expedites the procedure further while also saving time and money on platform testing.

4.2 Libraries used for project

4.2.1 Streamlit Web Framework

Simple creation and sharing of stunning, personalised web apps for data science and machine learning are made possible by the open source Python tool streamlit. It takes only a few minutes to design and launch a successful data app. Making open-source machine learning applications is simple for data scientists thanks to the Python-based streamlit toolkit. It is straightforward to read in and interact with a saved model thanks to an intuitive user interface. Additionally, model inputs can be changed through the UI by using sidebars, model outputs and descriptive text can be shown, data and model performance can be assessed, and much more. Using this straightforward platform, data science teams can rapidly and simply create free predictive analytics web applications. Data science and analytics are becoming more and more popular. Model deployment is one of the most crucial processes in the data science pipeline. In Python, there are various options for sharing our model. The disadvantage of using these frameworks is that it necessitates our proficiency in HTML, CSS, and JavaScript. These requirements had an effect on Adrien Treuille, Thiago Teixeira, and Amanda Kelly's design of "Streamlit.". With the aid of streamlit, deploying any Python project or machine learning model is now easy and independent of the front end. Using streamlit is simple. Using streamlight is straightforward.

4.2.2 Prophet

R and Python both support the future prediction method known as Prophet. It is quick and provides fully automated projections that scientists and analysts can modify manually. Prophet is an additive model-based statistical forecasting technique that takes into account non-linear trends, seasonality on a monthly, weekly, and daily basis, as well as effects from vacations. It works best when paired with statistical information from different historical periods and those that show significant seasonal influences. Prophet frequently handles outliers and is unaffected by missing data and trend changes. Prophet is a free open source project that has been made available by the Facebook Core Science team. It is made transferable using PyPI and cubic measure.

4.3 Accurate and fast

Many facebook applications employ the prophet to generate precise projections for goal setting and goal setting. We've found that it performs better than the alternative technique in the majority of cases. We frequently run models in stan so that we can get estimates in a matter of seconds.

4.4 Fully automatic

Without undertaking any manual labour, obtain an accurate forecast from jumbled data. Prophet accepts outliers, missing data, and large time series changes.

4.5 Tunable forecasts

Users of the prophet approach have a wide range of options for altering and modifying prophecies. By adding your subject-matter expertise to it and employing human-interpretable criteria, you can enhance your forecast.

4.6 Available in R or Python

There are several choices available to users of the prophet technique for changing and revising forecasts. You can improve your forecasts by using data that is easy for humans to understand. Utilize your subject-specific knowledge when evaluating.

4.7 Dataset Used

- Yahoo Finance

4.8 Software requirement specification

- Python
- Streamlit web framework

4.9 Hardware requirement specification

- Laptop

4.10 Output Result

1. LSTM Network

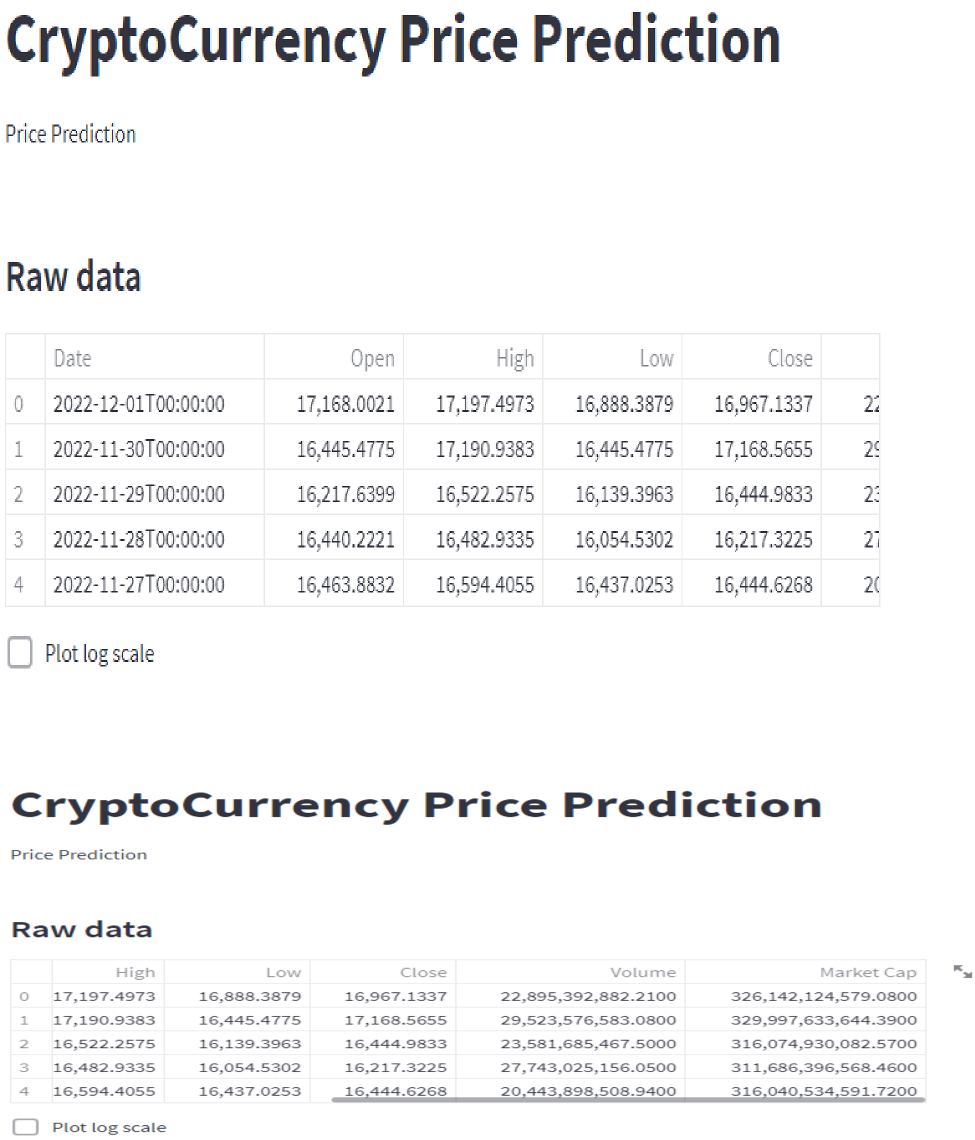
Figure 4.1 the LSTM network is displayed. Neural network architecture evolves in both directions using long- and bi-lstm. A bidirectional neural network enables both forward and backward input, whereas an LSM only permits forward input in percentage. Bi-directional systems preserve both past and future information by allowing data to flow in both directions. An example of a bidirectional lstm effect is the aforementioned result. The evaluation part also shows layer outputs and parameters for each layer in addition to total parameters, trainable parameters, and non-trainable parameters. In keras, non-trainable parameters (as shown in model.summary()) means the number of weights that are not updated during training with backpropagation.

```
_________________________________________________________________
Layer (type)                Output Shape              Param #
=================================================================
bidirectional (Bidirectiona  (None, 49, 98)           21952
l)

dropout (Dropout)           (None, 49, 98)            0

bidirectional_1 (Bidirectio  (None, 49, 196)          154448
nal)

dropout_1 (Dropout)         (None, 49, 196)           0

bidirectional_2 (Bidirectio  (None, 98)               96432
nal)

activation (Activation)     (None, 98)                0

=================================================================
Total params: 272,832
Trainable params: 272,832
Non-trainable params: 0
```

Figure 4.1: LSTM Network

2. Data Loading in Raw.

Each cryptocurrency has a different value at each of its open, high, low, and closure times. The data shown in the aforementioned graphic was obtained in March 2022. The range slider above shows the year vs. volume graph. The range slider was made using data from Yahoo Data Finance. Between March 13, 2022, and January 17, 2023, an API scraper used to acquire tick data gathered information, creating over 50,000 unique transaction records that included the price, trading volume, open, close, high, and low values.



	Date	Open	High	Low	Close
0	2022-12-01T00:00:00	17,168.0021	17,197.4973	16,888.3879	16,967.1337
1	2022-11-30T00:00:00	16,445.4775	17,190.9383	16,445.4775	17,168.5655
2	2022-11-29T00:00:00	16,217.6399	16,522.2575	16,139.3963	16,444.9833
3	2022-11-28T00:00:00	16,440.2221	16,482.9335	16,054.5302	16,217.3225
4	2022-11-27T00:00:00	16,463.8832	16,594.4055	16,437.0253	16,444.6268

	High	Low	Close	Volume	Market Cap
0	17,197.4973	16,888.3879	16,967.1337	22,895,392,882.2100	326,142,124,579.0800
1	17,190.9383	16,445.4775	17,168.5655	29,523,576,583.0800	329,997,633,644.3900
2	16,522.2575	16,139.3963	16,444.9833	23,581,685,467.5000	316,074,930,082.5700
3	16,482.9335	16,054.5302	16,217.3225	27,743,025,156.0500	311,686,396,568.4600
4	16,594.4055	16,437.0253	16,444.6268	20,443,898,508.9400	316,040,534,591.7200

Figure 4.2: Raw Data Loading

Figure 4.2 shows raw data extraction that data from dataset is loading with the till date and generate the raw data graph.

3. Forecast Plot for 365 Days

Values are trending in both the uphill and downhill directions, according to data obtained from Yahoo Finance. The range slider displays the day's vs. volume graph. The models are created using high frequency historical limit order book market data from Bitcoin. After extracting the best qualities, a mathematical representation that roughly corresponds to the data is discovered. The most well-

Figure 4.3: Forecast Plot for 365 Days

known and oldest cryptocurrency is Bitcoin, which was first made available as open source in 2009 by the enigmatic Satoshi Nakamoto. Since there is no need for a central clearing house or a trustworthy record-keeping body, Bitcoin operates as a decentralised type of digital commerce. Transactions on a public distributed ledger are verified and documented (the blockchain).Transaction blocks may be "chained" together to form an immutable record of all transactions that have ever taken place since they contain a SHA-256 cryptographic hash of earlier transaction blocks. The forecasting plot with the values for the upcoming 365 days is displayed by the range slider, which was created using data from Yahoo Data Finance. It will predict whether the numbers will rise or fall each month.The forecast plot for the following 365 days is shown in figure 4.3.

4. Forecast Component

The objective is to provide a solution that will enable us to steer clear of using the time series differencing approach since we are more interested in prices than in price changes as represented by integrated series of d-order. Each time series was broken into short, partially overlapping intervals to determine if there are any shorter time periods where the time series does not resemble a random walk. Each time regime contained a train and a test set, which made it possible to continue

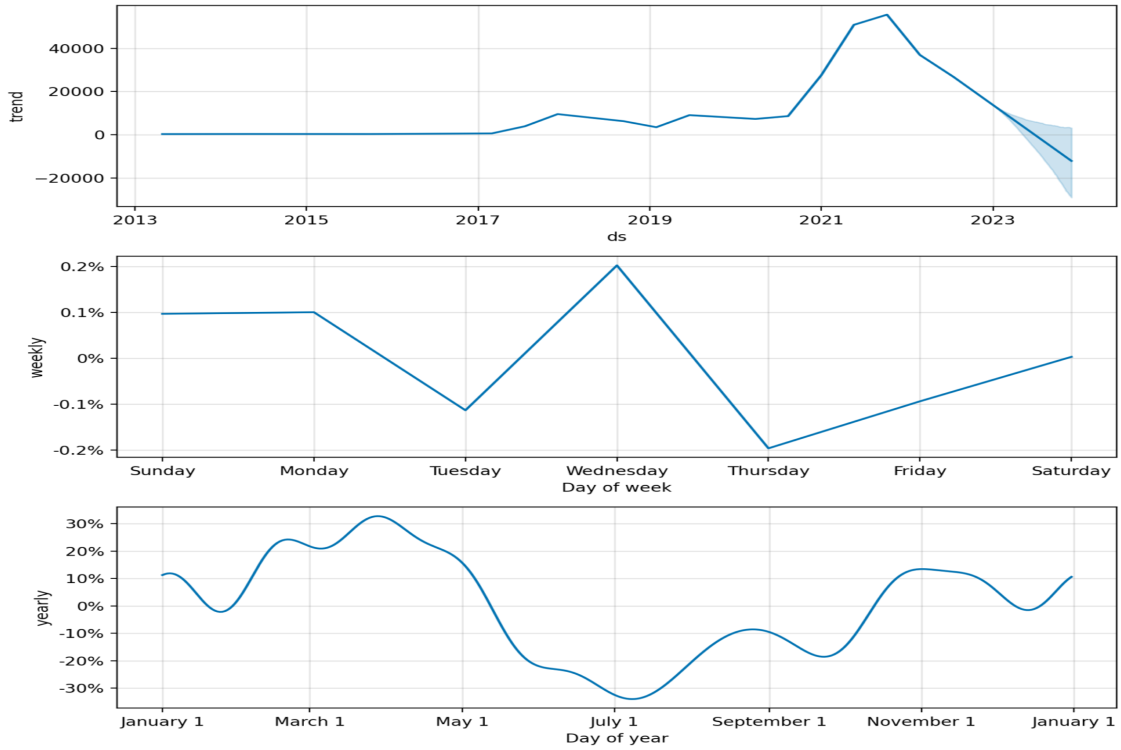


Figure 4.4: Forecast Component

the forecasting process. For each regime, we regularly gathered 200 observations, or 200 daily prices. A 120-point shift from the previous regime led to the start of the current one. A sharing agreement of 80 points between each regime and the one before it makes each 200 points broad. According to this analysis, there was a steady growth between January 2013 and January 2023, followed by a quick climb that peaked at the start of 2022. The lengths of the time series under study are different because of how the regime divide is created. 25% of the Bitcoin price datasets were used for testing, and the first 75% were used for training. This chart in figure 4.4 shows the bitcoin price distribution yearly, weekly, and monthly.

5. Closing Price Trend

A time series' trend may be understood and predictions can be made using an autoregressive model. Numerous elements, such as supply, demand, and regulation, have an influence on the time series of financial and economic statistics. Any financial market's complexity calls for a more complicated model. The optimal choice of the collection of significant endogenous variables determines how well the LSTM and regression forecasting models perform. After testing out several iterations of models and employing sensitivity analysis with various variables, delays, and time frames, a number of variables were made an effort as proxies to

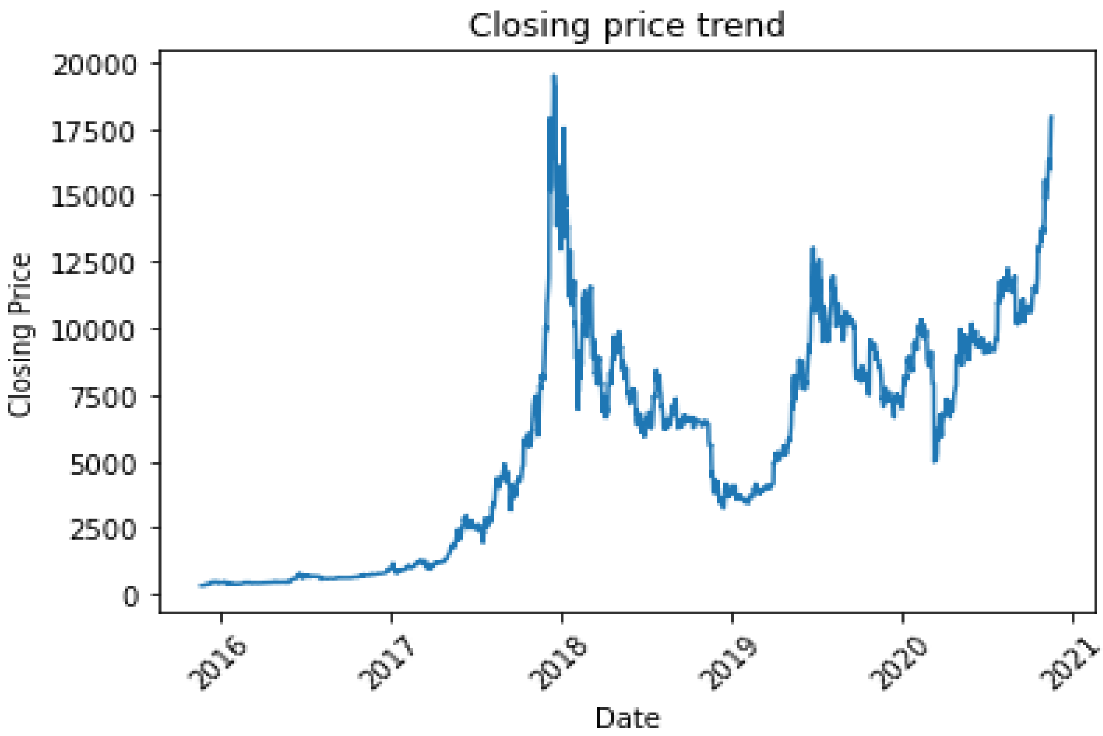


Figure 4.5: Closing Price Trend

reflect the price, demand, and supply of the BTC market, respectively. Traders typically use it as a reference point to contrast performance with prior expenses. The time period and closing price value are both displayed on the y axis. Figure 4.5 displays the closing price trend. At the height of business hours a bitcoin price damage is reported along with its value.

6. Time Series With Range Slider

Predicting future bitcoin values is crucial for investors. The ability to organise data in a way that enables accurate prediction is a strength of time series and related concepts. A time series is a collection of observations dispersed over space and time, typically at predetermined intervals. The most accurate method for identifying trends or even making future predictions is time series analysis. Analysis of cryptocurrencies is one of the common financial and market procedures made possible by time series visualisation. Values like as open, close, volume, high, low, and moving averages can all be displayed using this technique. These visualisations support long time scales, frequently reaching several years. Time series representations allow analysts to change the time scale and move around the data with ease. The investor can find the proper path using the trend chart. The range picker is a tool for selecting ranges that will be shown in the chart. The

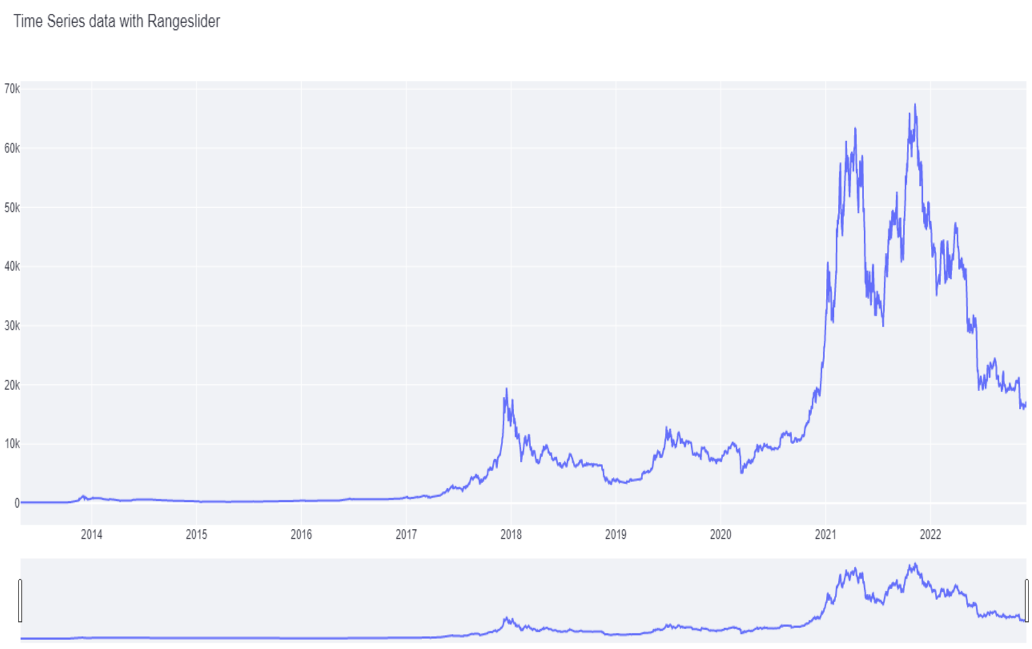


Figure 4.6: Time Series with range slider

price of bitcoin can be adjusted based on time intervals using the range slider. Figure 4.6 range slider for time series is displayed.

7. Confusion Matrix

F1 score:-

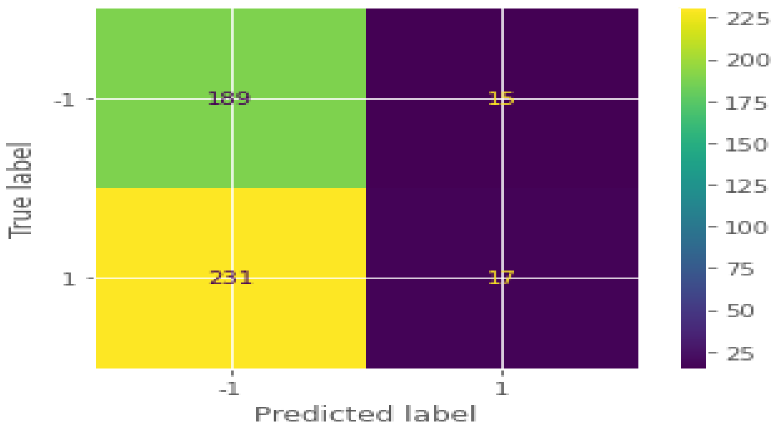
Utilizing the harmonic mean of recall and accuracy, the F1 score is calculated. Remember that the harmonic mean is a replacement for the more commonly used arithmetic mean.

Support:

Support may be calculated using the proportion of real answer samples that fall into each category of goal values.

Area Under Curve:-

Area Under Curve, or AUC (Area Under Curve) The Receiver Operating Characteristic (ROC), a performance measure for classification problems, is built on shifting threshold values. While ROC is a probability curve, as its name implies, AUC evaluates separability. In a word, the AUC-ROC assessment will show how well the model can distinguish between classes. Higher AUC values suggest better models. The anticipated label and genuine label are depicted in figure 4.7. It also demonstrates the accuracy, precision, and backing




```
              precision    recall  f1-score   support

          -1       0.45      0.93      0.61       204
           1       0.53      0.07      0.12       248

    accuracy                           0.46       452
   macro avg       0.49      0.50      0.36       452
weighted avg       0.49      0.46      0.34       452

45.57522123893805
```

Figure 4.7: Confusion Matrix

8. Simple Moving Average

The moving average is one of the fundamental indicators used in technical analysis. The Simple Moving Average is the easiest moving average to construct (SMA). In essence, it displays the mean price throughout the specified time frame. Because it is displayed bar by bar with a line that moves across the graph when the average value changes, the average is referred to as "moving" on the chart. SMAs are widely used to determine a trend's direction. If the SMA is increasing, the trend is upward. If the SMA is moving downward, the trend will also change. Usually, the long-term trend is represented by a 200-bar SMA. The intermediate trend is frequently determined using SMAs with 50 bars. Trends that appear more quickly can be detected using SMAs with shorter periods. In other words, it goes far beyond what an ordinary amount would require. Because it is displayed on the chart bar by bar, resulting in a line that moves as the average value changes, the average is referred to as "moving" for this reason.One of the fundamental indicators used in technical analysis is the moving average, and it can take many different shapes. The best moving average to construct is the SMA.

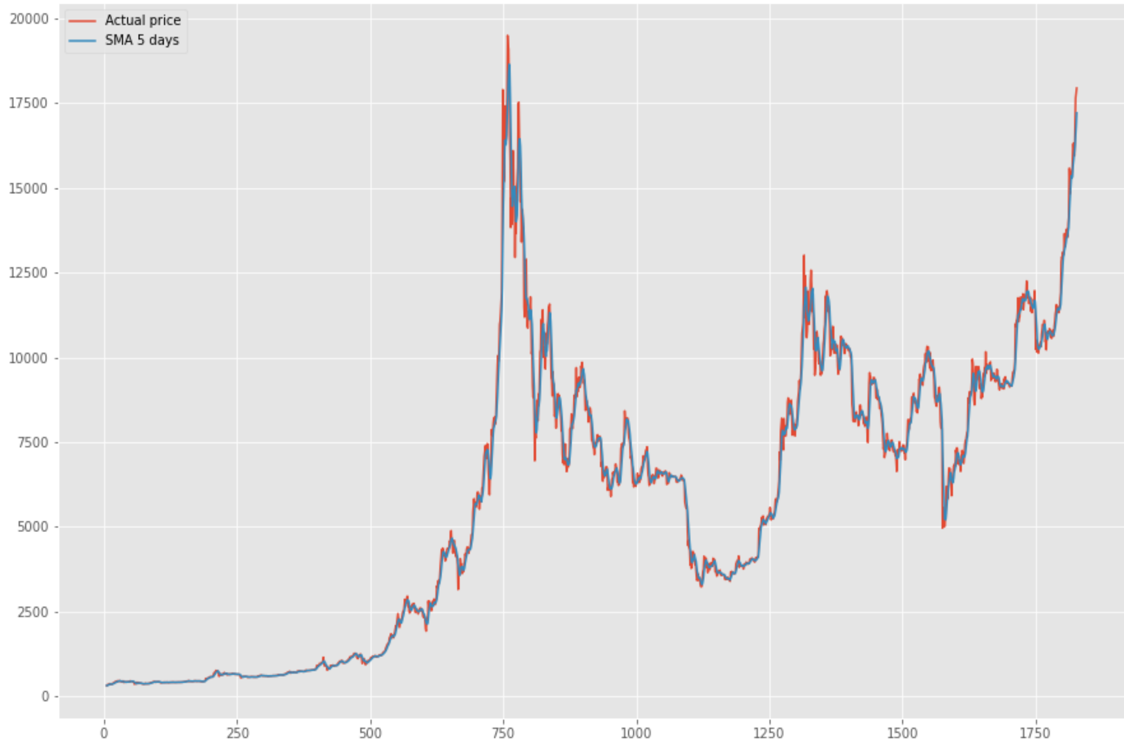


Figure 4.8: Simple Moving Average

The purest form of the moving average is shown in Figure 4.8.

9. Rolling Mean & Standard Deviation

Investors should pay close attention to larger returns from these types of products because bigger returns are primarily connected with an increased risk of future losses. An indicator fund, for instance, was purchased because it was thought to vary less than a growth fund. A moving average, also known as a rolling average or a running average, is a statistical method. Moving average is another term for it (MM). Without using one, it would be difficult to identify trends. However, by using one, you can. The standard deviation, which serves as the primary unit of volatility, is a measure of the spread or average deviation from which the data (bitcoin prices) deviates. In technical analysis for bitcoin, a moving average (MA) is a cryptocurrency indicator that is commonly used. In order to help smooth out price data, a moving average for a coin is made to offer a constantly updated price. The rolling mean and standard deviation are displayed on the y-axis, and time is displayed on the x-axis.

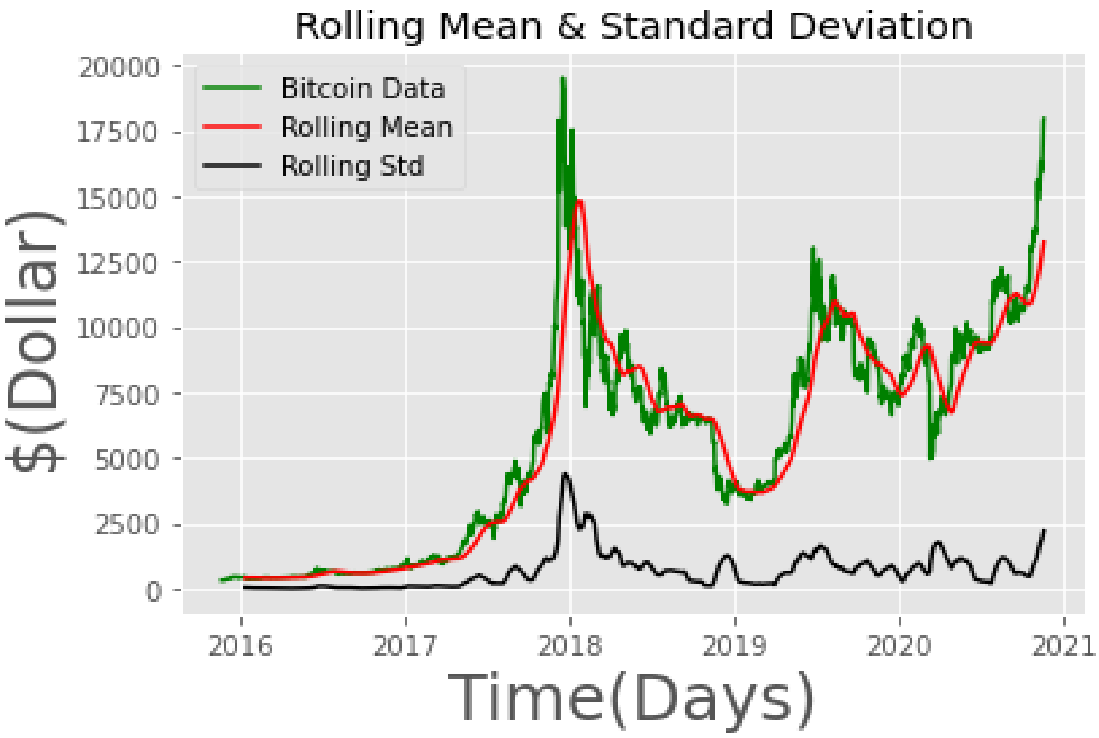


Figure 4.9: Rolling Mean & Standard Deviation

10. Expected VS Predicted Forecasting

Most seasoned experts routinely miss their predictions of bitcoin values or fluctuations by 60% to 80%. To effectively predict the price range for cryptocurrencies and make investment decisions as a result, investors should consider a number of variables. When projecting the price of bitcoin for the next day, one of the most important determining variables is often the human intelligence component. A significant contrast between an expectation and a forecast is the effect it has on behaviour. If we prepare for them, recessions and bear markets won't startle us. Investors can make financial decisions based on a comparison of predicted and anticipated bitcoin values. The initial close price is shown on the green line. The anticipated price is shown by the orange line. Figure 4.10 displays forecasting of expected vs. predicted. There is no correct way to predict the cryptocurrency prices with 100% accuracy.

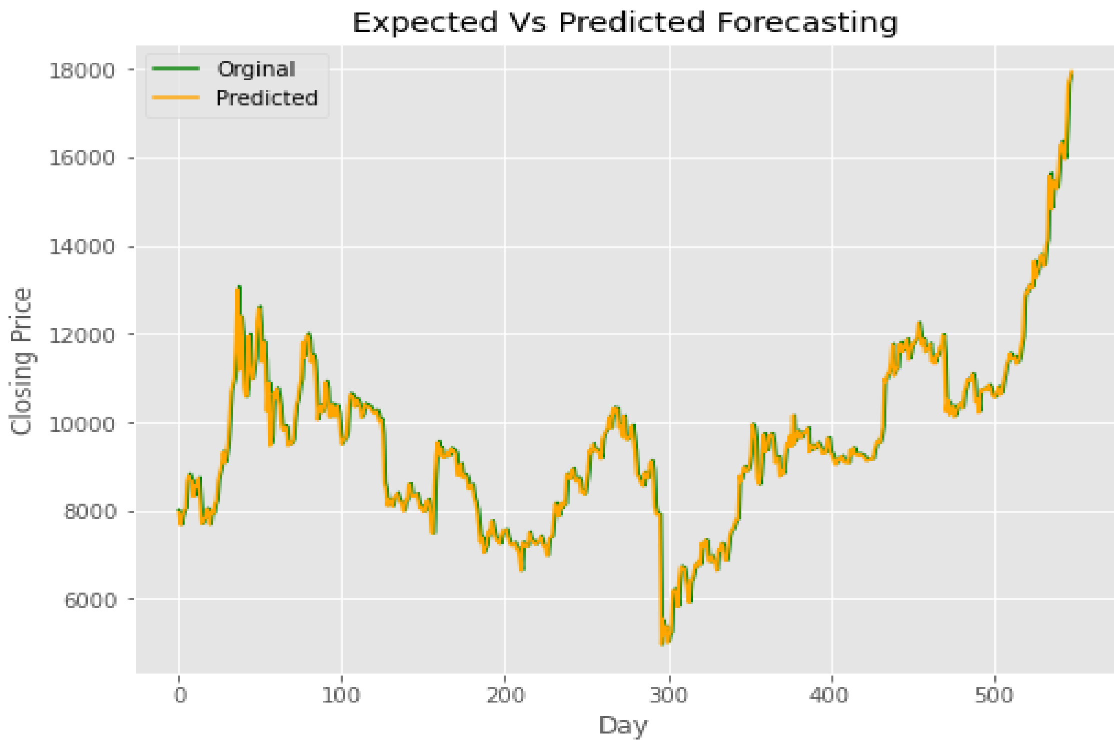


Figure 4.10: Expected VS Predicted Forecasting

11. F1 Score

The F1 scores are contrasted in figure 4.11. Harmonically averaging recall and accuracy yields the F1 score. Do not forget that the harmonic mean might be utilised in place of the more widely used arithmetic mean. Typically, it is useful for calculating the average rate. We calculate the mean of recall and accuracy for the F1 score. Because the F1 score is the average of the two, precision and recall are given equal weight in the score. If a model has good precision and recall, it will have a high F1 score.

- A model will have a low F1 score if its accuracy and recall are both inadequate.
- The F1 score will be average if a model's accuracy or recall are subpar but the other is great.
- Its major objective is to evaluate the performance of two classifiers. Assume that classifiers A and B are more accurate and recallable. It is possible to determine which classifier in this circumstance produces better results by comparing their F1-scores.

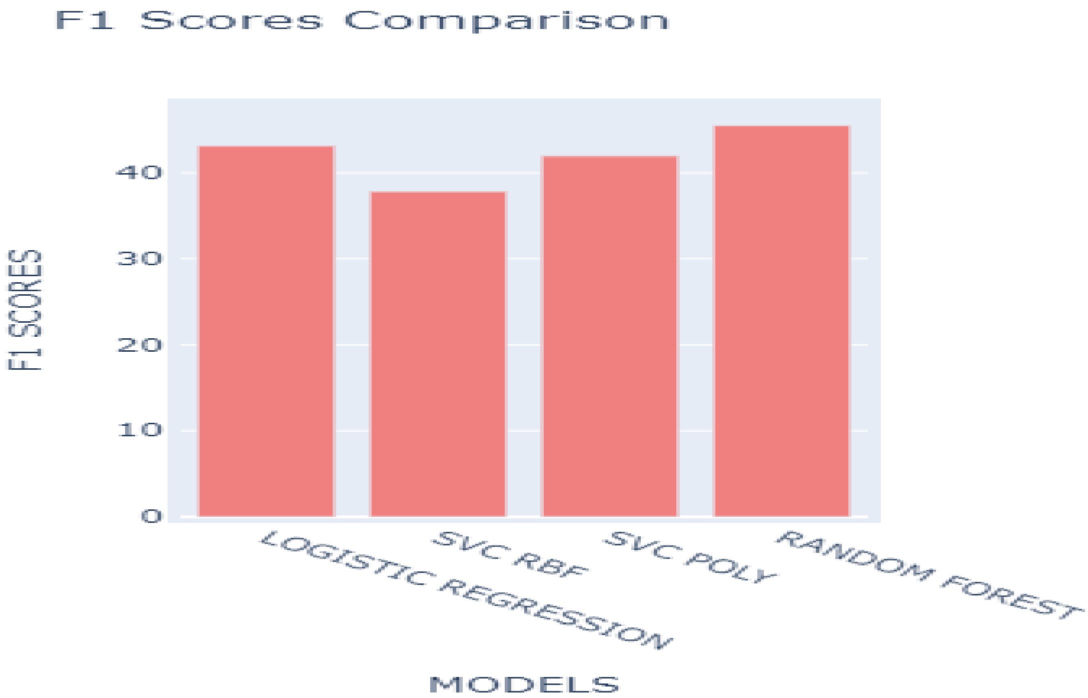


Figure 4.11: F1 Score Comparison

One of the most crucial evaluation measures in machine learning is the F1-score. By combining two metrics, recall and accuracy, that would otherwise be at odds, it elegantly summarises the prediction performance of a model.

Chapter 5

Conclusion

5.1 Conclusion

- If we train on more diversified data sets, the outlook might be better.
- In order to increase the precision of a graph, this article looks at trends in the share prices of various companies across a wide range of time periods.
- This framework states that it can be used by a variety of organisations to support research and long-term growth projections.
- By adding additional variables, such as political stability, election outcomes, and the state of capitalism, the prediction's accuracy may be improved.
- Because bitcoin values are fundamentally variable and dependent on numerous factors that form complicated patterns, forecasting gains on the securities market can be challenging.
- The only options in the historical data that is available on yahoo finance that are insufficient are the number of shares listed, the high, low, open, close, and adjacent closing prices for bitcoin.
- The LSTM compares and anticipates the factors influencing the price of bitcoin the next day. For the prediction study in this system, which is now in use, we used bitcoin.
- By utilising the already-existing variables, new variables are developed to improve the precision of the projected result. Here, we've looked at bitcoin and forecasted its price for the next 12 months.

5.2 Future Scope

- Display day by price of bitcoin when predicting the future price.
- Now this system is only limited to bitcoins so future approch is to apply this system to other coins also.
- Improve the accuracy of the system.

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LIST OF PUBLICATIONS ON PRESENT WORK

[1] Sabira Mulla, Prof.S.R.Jagtap "Crypto Currency Price Prediction Using Deep Neural Networks " "International E-conference on Innovation and Emerging Trends in Engineering Science and Management "

[2] Prof S.R. Jagtap , Sabira S. Mulla "Crypto Currency Price Prediction Using Deep Neural Networks " IEEE Transaction on learning Technologies ISSN 1939-1382 (Status :- Under Review)

ISBN : 978-93-91535-38-4

Crypto Currency Price Prediction Using Deep Neural Networks

Sabira Mulla, Prof. S. R. Jagtap

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1.1 Introduction

Crypto currency may be a new variety of quality that has emerged as results of the advancement of financial technology and it's created a giant chance for researches. Cryptocurrency worth forecasting is troublesome because of worth volatility and dynamism. Round the world, there are a whole lot of crypto currencies that are used. Paper [1] proposes 3 styles of perennial neural network (RNN) algorithms want to predict the costs of 3 styles of crypto currencies, particularly Bit coin (BTC), Litcoin (LTC), and Ethereum (ETH). The models show wonderful predictions counting on the mean absolute share error (MAPE). Results obtained from these models show that the gated perennial unit (GRU) performed higher in prediction for every kind of crypto currency than the long remembering (LSTM) and Bifacial LSTM (bi-LSTM) models. Crypto currency i.e. bit coin. The recent trend in value prediction technologies is that the use of machine learning that makes predictions supported the values of current value indices by coaching on their previous values. Machine learning itself employs totally different models to create prediction easier and authentic. Our Main focuses on the utilization of Regression and LSTM based mostly Machine learning to predict values.

1.2 Motivation of the present work

The rise in crypto currencies price has contributed to the decentralization of authority, lowering management amongst countries. The wide worth varies of digital currencies highlights the need for reliable preparation for predicting the currency's worth. A new model may be a state of affairs during which this paper presents are placement manner of forecasting digital price for cash by considering many variables, such as stock exchange capitalization, volume, distribution, and high-end delivery.

1.3 Techniques

Bitcoin runs on a peer-to-peer basis and is a decentralized cryptocurrency. It uses encryption and anonymity for cryptography. Bitcoin is the top-ranking cryptocurrency centered on the internet. The People most encounter Bitcoin due to anonymity and transparency in the system, among the widespread cryptocurrencies available onthe market. Bitcoin becomes popular because of its price fluctuations. Cryptocurrency has emerged as a crucial element in companies and stock sector opportunities in the stock industry over the last decade. The accurate and consistent forecast will help investors in cryptocurrency make the right investment decisions and

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ISBN : 978-93-91535-38-4

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Crypto Currency Price Prediction Using Deep Neural Networks

Sabira Mulla [*], **Prof. S. R. Jagtap** [**]

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Abstract- Crypto Currency is any form of digital currency that only exists digitally means online mode, this system has no central issuing or regulating authority but instead uses a decentralized model system, and this is used to record transactions and manage the issuance of new units, which relies on cryptography system to prevent counterfeiting and fraudulent transaction. Crypto currency is decentralized medium digital money that's based on blockchain technology. Now people are familiar with the most popular versions, Bit coin and Ethereum, but there are more than 5,000 different crypto currencies in circulation. Bitcoin was established in 2009 and, for a lot of than two years, was the only Blockchain-based crypto currency's crypto currency is a standard medium of exchange that is digital currencies in encrypted and decentralized mode . As like US dollar, no central authority manages and maintains a crypto currency's value. Instead, these tasks are broadly distributed among cryptocurrency users via the internet. In addition to buying common goods and services, you can also invest in cryptocurrencies, just like you would in other assets.

Index Terms- Cryptocurrency, Price Prediction, BitCoin

I. INTRODUCTION

Cryptocurrencies may be a new quality that has emerged due to advancements in financial technology, and they have created a lot of research opportunities. Due to cryptocurrency's volatility and dynamism, it is difficult to forecast its worth. Cryptocurrencies are widely used around the world. Three styles of perennial neural network (RNN) algorithms are proposed in this paper. Estimate the cost of 3 types of cryptocurrencies, including Bitcoin (BTC), Litcoin (LTC), and Ethereum (ETH). Based on the mean absolute error (MSE), the models produce excellent predictions. Based on these algorithms and models, gated perennial units (GRU) performed better in prediction than long-remembering (LSTM) and bi-LSTM models for every type of cryptocurrency. Therefore, it can be considered the most effective formula. GRU presents the foremost correct prediction for LTC with MAPE percentages of zero.2454%, 0.8267%, and 0.2116% for BTC, ETH, and LTC, severally. For BTC, ETH, and LTC, the MAPE percentages of the bi-LSTM algorithm are five.990%, 6.85%, and 2.332%, respectively. As a whole, the prediction models performed well during this Paper represent correct results near the particular costs of cryptocurrencies. The importance of getting these models is that they will have important economic ramifications by serving investors and traders for the endpoint pinpoint cryptocurrency sales and buying. In Crypto Currency value Prediction, the aim is to predict the long-run price of the cryptocurrency, i.e., bitcoin. The recent trend in value prediction technologies is that machine learning that makes predictions supports the values of current value indices by coaching on their previous values. Furthermore, machine learning employs different models to create predictions that are more accessible and more authentic—our Main focus is on using Regression and LSTM-based, mostly Machine learning to predict value values.

II. Literature Review

It is one of the computing models that can predict longer-term supported past information through machine learning (ML). Since ML-based models produce almost or exactly the same results as the actual results, and they increase their accuracy, they have numerous advantages over alternative foretelling models. Neural networks (NN), support vector machines (SVM), and deep learning are examples of machine learning. Crypto currency improves the effectiveness of a portfolio in two ways, according to the authors. The primary goal is to reduce quality deviation, while the secondary goal is to provide investors with more allocation options. Depending on the capitalist's risk tolerance, the best cryptocurrency allocation ranged from five to twenty. To predict statistics, the authors apply two machine learning algorithms, random forests (RF) and random gradient boosting machines (SGBMs). Using the mil ensemble technique, Bitcoin values can be predicted. To reduce the risks associated with the investment method, the call-making method must make the right decision at the right time. A hybrid crypto currency prediction system based on LSTM and GRU is presented in this paper, targeting Litecoin and Monero[2]. The authors combine recreational vehicle information using minute-sampled Bitcoin returns over three-hour periods. The heterogeneous auto-

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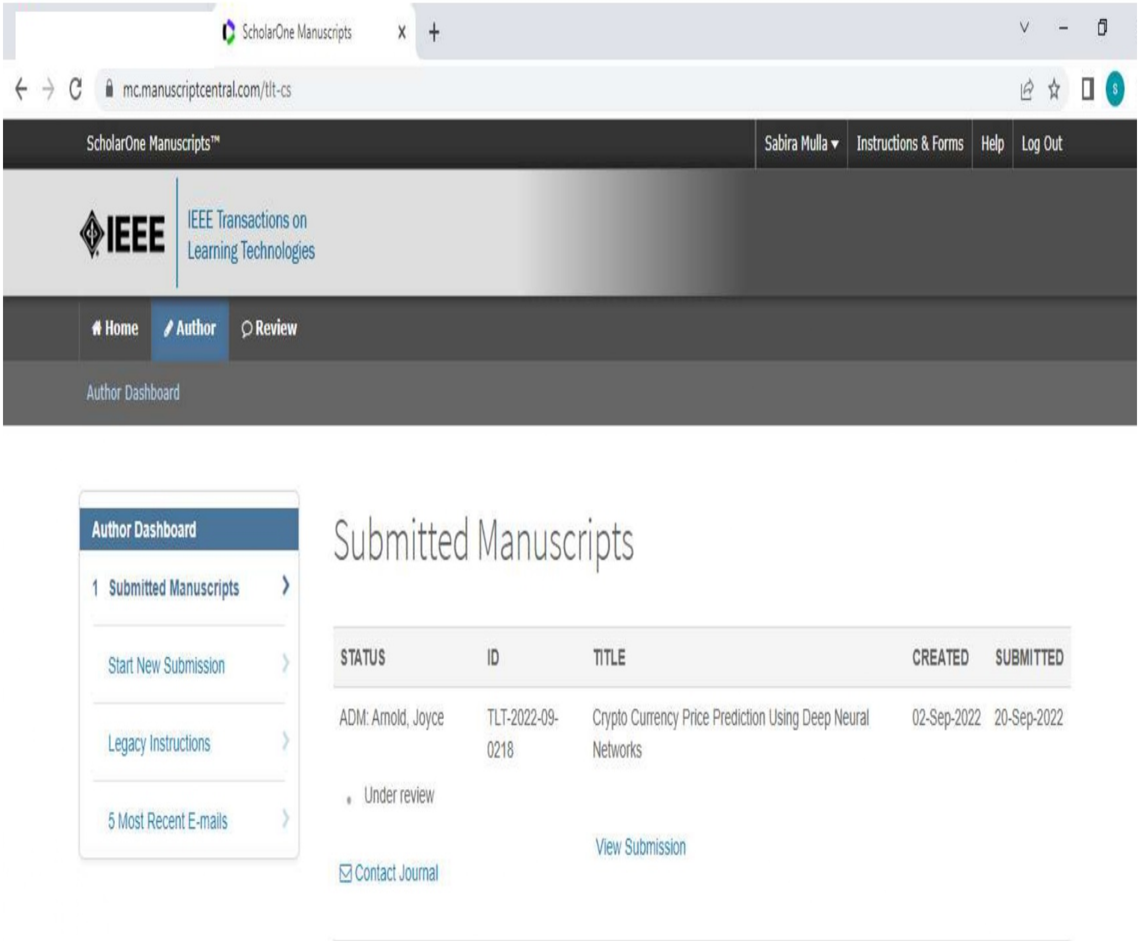

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SYNOPSIS OF M. Tech. DISSERTATION

1. Name of Program : M.Tech Electronics

2. Name of Student : Sabira Samad Mulla

3. Enrollment No. : 2023007

4. Date of Registration : 13/12/2021

5. Name of Guide : Prof. S.R.Jagtap

6. Sponsor's Detail (if any) : nil

7. Proposed Title : Crypto Currency Price Prediction Using Deep Neural Networks

Approved Copy of Synopsis
Page...1.../..9.....

8. Synopsis of Dissertation Work

8.1 Relevance:

In Crypto Currency Price Prediction, the aim is to predict the future value of the crypto currency i.e. bit coin. The recent trend in price prediction technologies is the use of machine learning which makes predictions based on the values of current price indices by training on their previous values. Machine learning itself employs different models to make prediction easier and authentic. Our main focus is on the use of Regression and LSTM based machine learning to predict price values.

The rise in crypto currencies price has contributed to the decentralization of authority, lowering management amongst countries. The wide worth vary of digital currencies highlights the need for reliable preparation for predicting the currency's worth. A new model may be a state of affairs during which this paper presents are placement manner of forecasting digital price for cash by considering many variables, such as stock exchange capitalization, volume, distribution, and high-end delivery.

8.2. Literature Review:

Hitam et al. [1], proposed a machine learning (ML) may be a kind of computing that may predict the longer term supported past information. ML-based models have numerous blessings over alternative foretelling models as previous analysis has shown that it not solely delivers a result that's nearly or precisely the same because the actual result, however it conjointly improves the accuracy of the result. Samples of machine learning embody neural networks (NN), support vector machines (SVM), and deep learning.

Yanuar Andrianto et al [2], proposed to demonstrate that incorporating crypto currency into a portfolio improves its effectiveness in two ways. The primary is to cut back the quality deviation, and therefore the second is to produce investors with additional allocation choices. The best crypto currency allocation was reported to be within the vary from five-hitter to twenty, betting on the risk tolerance of the capitalist. The authors of concentrate on statistic information foretelling in particular and apply 2 machine learning algorithms, random forests (RF) and random gradient boosting machine (SGBM). The results show that the mil ensemble technique will be wont to anticipate Bitcoin values. The call-making method must build the suitable decision at the correct time, reducing the risks related to the investment method. In [28], a hybrid cryptocurrency prediction system supported LSTM and GRU is bestowed, specializing in 2 cryptocurrencies, Litecoin and Monero.

Derbentsev et al. [3], proposed a minute-sampled Bitcoin returns over three h periods to combination RV information. a range of machine learning strategies, together with ANN (MLP, GRU, and LSTM), SVM, and ridge regression, were accustomed predict future values based on past samples, that area unit compared to the heterogeneous auto-regressive realized volatility (HARRV) model with optimized lag parameters. The findings show that the suggested system properly predicts costs with high accuracy, indicating that the strategy may be accustomed forecast costs for a range of crypto currencies.

Mohammad J. Hamayel et al [4], proposed a traditional support vector machine and regression toward the mean strategies to forecast Bitcoin values. This analysis takes into consideration a statistic prediction created from everyday Bitcoin closing costs for the creation of Bitcoin prediction model.

Joost Verbraeken et al [5], proposed a new machine learning techniques to deal with each a multivariate analysis technique that relies on extremely related characteristics and a deep learning mechanism that uses a conjugate gradient mechanism in conjunction with a linear seek for BTC worth prediction.

Deepak Kumar et al [6], proposed a value movements of Bitcoin, Ethereum, and Ripple area unit analyzed. The authors utilize powerful computer science frameworks, together with a totally joined artificial neural network (ANN) and an extended STM (LSTM) perennial neural network, and they discovered that ANN depends additional on long history, whereas LSTM depends additional on short term dynamics, implying that LSTM is additional economical at extracting meaning info from historical memory than ANN.

Dennys C et al [7], proposed a prediction based on Bitcoin daily worth prediction with high-dimensional information reveals that logistical regression and linear discriminant analysis achieve associate degree accuracy of sixty six. On the opposite hand, surpassing (a subtle machine learning algorithm) outperforms the benchmark results for daily worth prediction, with statistical techniques and machine learning algorithms having the best accuracies of 66% and 65.3%, severally.

8.3. Proposed Work:

8.3.1 Objectives:

1. To review the current literature to understand the existing methods
2. To analyze the existing methods for finding crypto currency prediction with the Current Date
3. To collect and train the data
4. To develop new algorithms for price prediction and find the best result
5. To test the accuracy of the developed algorithm using confusion Matrix
6. To validate the results

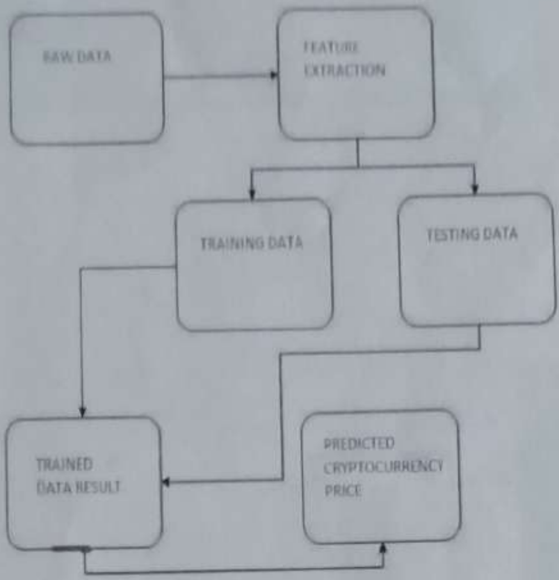

Fig1. Proposed block diagram

Bitcoin price data (BTC-USD) will be initially collected from Kaggle. The data collected will cross checked with that from Coin base in order to avoid any unwanted discrepancies. Machine Learning is the most suitable technique which can be used here to predict Bitcoin crypto currency prices prediction. The model to be built has to achieve several goals in order to produce a near to accurate prediction. This included selecting the framework which could produce good prediction accuracy, take in consideration of other parameters in its prediction algorithm and be trainable. Keeping these goals in mind, several different frameworks will be tested.

Fig1. Shows the block diagram of the proposed work. The Proposed architecture shows that feature extraction of the collected data will be done. After that data will be trained and tested to obtain trained data. Finally crypto currency price will be predicted with the help of trained data.

8.4.1. Activity Chart:

Fig2. Shows an activity chart for completion of the dissertation work

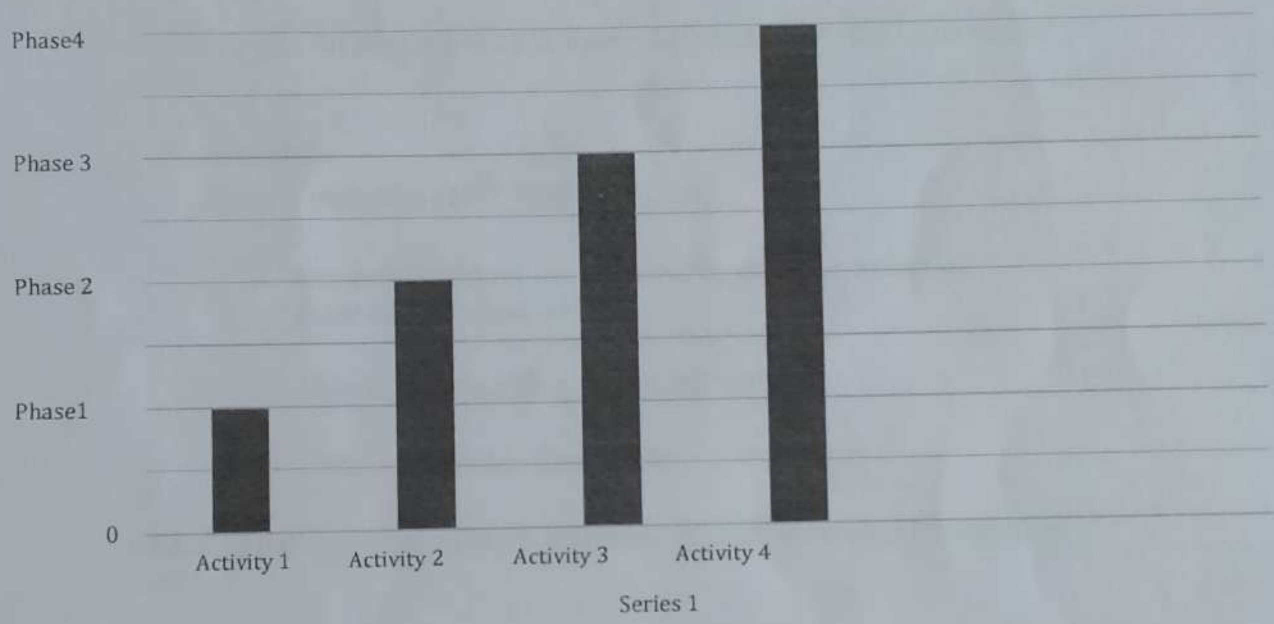

Fig2. Activity Chart

The Phases and activities are as follows:-

- **Activity1:**
  Phase 1 activities: (15th Nov-29th Jan)
    - Literature Survey
    - Identifying various applications which use technique for crypto currency price prediction
    - Synopsis Writing

-Gap of 10 days for Pending work & Review of work done after Dissertation phase1.

- **Activity2:**
  Phase 2 activities (10th Feb-28th Feb)

  - Analyzing existing techniques for crypto currency price prediction
  - Performing the some modules.

-Gap of 10 days for Pending work & Review of work done after Dissertation phase2.

- **Activity3:**
  Phase 3 activities (10th Mar-12th Apr)

  - Implementation of the proposed system and collecting experimental observations.
  - Developing algorithm for overall system
  - Checking the algorithm result

-Gap of 10 days for Pending work & Review of work done after Dissertation phase3.

- **Activity4:**
  Phase 4 activities (21th Apr-31th May)

  - Comparison and analysis of experimental results of proposed method and earlier method.
  - Paper publication
  - Report writing

9. Facilities Available:

The following facilities to carry out dissertation work are available at Rajarambapu Institute of Technology, Rajaramnagar.

1. Internet Facility
2. Advance digital library(IEEE and other journals)

10. Expected Date for Completion of Work: April 2022

11. Approximate Expenditure: 15000/-

Date: 1/2/2022

Place: Rajaramnagar

Sabira Samad Mulla

Student

Dept. of E & TC Engg. RIT APPROVED COPY of Synopsis M. Tech Electronics

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Guide

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PAPER NAME

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AUTHOR

sabira mulla

WORD COUNT

8023 Words

CHARACTER COUNT

42812 Characters

PAGE COUNT

44 Pages

FILE SIZE

809.9KB

SUBMISSION DATE

Jan 7, 2023 11:58 AM GMT+5:30

REPORT DATE

Jan 7, 2023 11:59 AM GMT+5:30

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