CHAPTER 1

INTRODUCTION

1.1 Overview

Social platforms have gained a great deal of popularity in recent years, primarily due to the natural and continuous human desire for interaction and the ease with which these virtual connections can be formed and maintained. The social networks communities currently offer a vast source of information and opinions on any topic, exploiting this data becoming a priority in many research and language processing activities. The virtual currency represents an alternative means of exchange, consisting of various types of the decentralized cryptocurrencies, each one having its particularities and value. The information flow on the topic of virtual currency is characterized by diversity, the nature of the opinion and sentiment fluctuating based on many variables. From a technical standpoint, the sentiment analysis is part of the natural language processing and involves training a classifier on a labeled corpus, in order to identify and establish attributes / features which can afterward be used in processing new input data and evaluating its nature. Based on these, the study proposes a solution for analyzing the sentiment in texts extract from twitter api and with historical price data we going predict price with the use of LSTM model.

1.2 Objective

To Collect Twitter data and store in a suitable from.

To pre-process and extract useful features from data.

To train a Model on these extracted features.

To detect and predict the trends and movement of a crypto currency.

To evaluate model-performance and improve it.

1.3 Purpose, Scope, and Applicability

1.3.1 Purpose

Purpose of this project is to,

Help traders to trade cryptocurrency based on trends.

The popularity of a particular currency can be determined.

The community of particular coin can be targeted and engaged.

1.3.2 Applicability

The project is applicable for all types of coins, including alt-coins and other big name crypto currencies. This project is applicable for vendors who need insights regarding any specific cryptocurrency

1.4 Organization of Report

Chapter 2 of this document describes the Literature Survey. It provides details about the existing system, the limitations that the existing system experiences and the proposed system for the project

Chapter 3 of this document describes the Requirement Engineering. It includes an overall description and specific requirements. The overall requirement is classified as Software and Hardware Tools Used, The Conceptual/ Analysis Modeling, Use case diagram, Sequence diagram, Activity diagram and State chart, Chart Diagram. Specific requirements are classified as hardware requirements, software requirements, functional requirements and non-functional requirements.

Chapter 4 is the Gantt Chart which is a bar chart showing the project schedule.

Chapter 5 describes the Applications of the proposed work.

Chapter 6 describes the Conclusion of the project

CHAPTER 2

LITERATURE SURVEY

A literature survey or literature review in a project report is that section that shows the various analyses and research made in the field of your interest and results already published, taking into account the various parameters of the project and the extent of the project.

2.1 Summary of Papers

Jarmain Kaminski, Peter A.Gloor - Nowcasting the Bitcoin Market with Twitter Signals[1]: In this paper,the authors collected162,000 tweets in the timeframe between November 23rd 2013 until March 7th 2014. They figured that there were over 300M impressions.To get “emotional” tweets they used couple of keywords related to crypto. Then they pooled them into four classes. After doing this they collected market data from couple of popular database website on close price,interday price etc. With those correlate between sentimental value with all the market data individually ,we get the result Intraday measurements of Twitter sentiments may contribute to determine the movement of Bitcoin close price and volume. While the predictive validity of this work is very limited, it may at least confirm the possibility of ”Nowcasting”.

Drawback: This paper deal is Higher Bitcoin trading volume causes more signals of uncertainty. Higher trading volume leads to the interpretation that emotional sentiments rather mirror the market than that they make it predictable.

Aniruddha Dutta, Saket Kumar, M Basu - A gated recurrent unit approach to bitcoin price predict [2]:In this paper authors they practiced recurrent neural network to predict the future price ,they used gru so that it works with fewer tensor operation and speedier than lstm. They performed feature engineering to obtain independent variables for future prediction.They obtained time series data from bitcoincharts.com. also collected google trends search data as it will also has potential to predict prices.The very next step is to extract the features ,here they correlated bitcoin price with exogenous feature with the graph they got they evaluated it and features choose with respect to that.For these extracted feautres trained over simple neural network (NN) , LSTM with dropout,

GRU , GRU with a recurrent dropout , and GRU with dropout and recurrent dropout and calculated validated loss.

Drawback : This techniques is that Deep models require accurate training to yield results. But data limited in crypto market.

J Ramteke, Samarth Shah, Aadhil Shaik -Election result prediction using Twitter sentiment analysis[3]: Twitter data for two candidates – namely Donald Trump and Hillary Clinton were collected for the dates March 16th, 2016 and March 17th, 2016 using twitter stream API.The tweets were stripped off special characters like '@' and URLs to overcome noise. Additionally, in the Machine Learning modules, to improve the classifier accuracy, we employ the TF-ID) technique, to identify terms which are more relevant to sentiments. After preprocessing data Vader takes a sentence as input and provides a percent value for three categories positive, neutral and negative and compound. Various algorithms for natural language processing and more specifically sentiment analysis are available today. They used two algorithms, Multinomial Naïve Bayes and Support Vector machines to determine the polarity of tweets.They got accuracy of 0.85 and 0.8 accuracy.

Drawback : On Contrary to popular poll results, the candidates had a very close negative to positive sentiment ratio.

Reaz Chowdhury, M.Arifur Rahaman, M R C Mahdy, M Sohel Rahman-Predicting and Forecasting the Price of Constituents and Index of Cryptocurrency Using Machine Learning[4]: dataset includes seven-day week daily data which we have obtained from https:\\coinmarketcap.com. The constituents and predictive models. We have considered seven attributes and divided our data into two subsets- testing and training.They have used the widely used software called RapidMiner as it supports all steps of a data mining process. In RapidMiner software, for performing data analysis usually graphs, plots, charts and tables are used in which one can easily visualize the output and also compare between one or more attributes and models. For a machine to predict and forecast the future close price of any cryptocurrency, it is essential to train the machine to learn from the given dataset. Based on these datasets, models will be created applying different algorithms and thus the prediction/forecasting task will be accomplished accuracy and RMSE using gradient boosted trees model are 0.900 and 0.001, and 0.924 and 0.002 using ensemble learning.

Drawback: Is that the Accuracy was low for the model forecasting the price, when compared to BT low Prediction, considering KNN is being used on a very large data set.

Vytautas Karalevicius- Bitcoin price prediction and trading using static twitter data set [5] : The database of relative news articles as well as blog posts has been collected for the purpose of this research. Hence, each article has been given a sentiment score depending on the negative and positive words used in the article This paper has identified that interaction between media sentiment and the Bitcoin price exists, and that there is a tendency for investors to overreact on news in a short period of time.While sentiment analysis of Twitter posts as a predictor of the Bitcoin price has been conducted in the past, this research does not have any analog because psycho-semantic dictionaries have not been applied earlier in the Bitcoin research.

Drawback: Usage of static limited data and data is restricted to bigger coins only.

Galen Thomas Panger- Emotional analysis in Social media [6]: The role of emotion in social media has been the subject of considerable research and media attention. But while stereotypes about the emotional profile of status updates - that they are overly-positive, or overly-angry - Further, although researchers have made numerous efforts to use the emotions we express in status updates to make inferences about our emotional lives -generating national happiness indices, predicting mental illnesses and evaluating emotional outcomes of experimental interventions — little is known about the validity of these inferences at the individual level, and researchers have largely ignored the impact of self-presentation and privacy concerns on validity. Finally, while debate continues about the emotional impacts of browsing social media in the course of day-to-day life, researchers have focused only on a limited set of emotions, rather than investigating the range of human emotion., presenting three analyses regarding (1) the emotions we express in social media, (2) what can be inferred about our emotional lives in general based on how we express ourselves in social media, and (3) the emotional experience of browsing social media. I conduct experience sampling for one week with participants in a Facebook sample (N = 344) and Twitter sample (N = 352), gathering data about their day-to-day emotional lives. I then compare this data to participants'ratings of the emotional contents of their most recent status updates so as to reveal the distinct emotional profile of status updates and address questions regarding the validity of inferences. Data from experience sampling is also used to reveal the emotional experience of browsing social media.

Mahdi H. Miraz,Maaruf Ali-Applications Of Blockchain Technology beyond Cryptocurrency [7]:The application of the Blockchain concept and technology has grown beyond its use for Bitcoin generation and transactions. The properties of its security, privacy, traceability, inherent data provenance and time-stamping has seen its adoption beyond its initial application areas. The Blockchain itself and its variants are now used to secure any type of transactions, whether it be human-to-human communications or machine-to-machine. Its adoption appears to be secure especially with the global emergence of the Internet-of-Things. Its decentralized application across the already established global Internet is also very appealing in terms of ensuring data redundancy and hence survivability. The Blockchain has been especially identified to be suitable in developing nations where ensuring trust is of a major concern. Thus the invention of the Blockchain can be seen to be a vital and much needed additional component of the Internet that was lacking in security and trust before. BC technology still has not reached its maturity with a prediction of five years as novel applications continue to be implement globally.

Drawback: Using blockchain technology is the expensive gas fees Environmental hazard

Unregulated Market i.e, there is no proper law so there is high chance of getting scammed.

Stefano Cavalli, Michele Amoretti-An Advanced CNN based multivariate data analysis for bitcoin trend prediction Forecasting [8]: In this work, we illustrated a novel approach for bitcoin trend prediction based on 1D CNN. We proposed a methodology for building datasets whose items are characterized by different types of features: bitcoin historical values and financial indicators, Twitter sentiment analysis, Bitcoin blockchain information. We presented a cloud-based system with a highly efficient distributed architecture, which allowed us to collect a huge amount of data and to create thousands of different datasets. We showed that the 1D CNN model is used by that company with assumed initial investment of X units. The conclusion was that the proposed 1D CNN model increases the profit when the bitcoin trend is bullish and reduces the loss when the trend is bearish.

Drawback : Coins with low market capitalization will no yield sufficient results and the data is not real time so its not really helpful for user to prefer.

Jethin Abraham, Daniel Higdon, John Nelson, Juan Ibarra- Cryptocurrency Price Prediction Using Tweet Volumes and Sentiment Analysis [9]: this paper, we present a method for predicting changes in Bitcoin and Ethereum prices utilizing Twitter data and Google Trends data. Bitcoin and Ethereum, the two largest cryptocurrencies in terms of market capitalization represent over $160 billion dollars in combined value. However, both Bitcoin and Ethereum have experienced significant price swings on both daily and long term valuations. Twitter is increasingly used as a news source influencing purchase decisions by informing users of the currency and its increasing popularity. As a result, quickly understanding impact of tweets on price direction can provide a purchasing and a trader. By analyzing tweets, we found that tweet volume, rather than tweet sentiment (which is invariably overall positive regardless of price direction), is a predictor of price direction. By utilizing a linear model that takes as input tweets and Google Trends data, we were able to accurately predict the direction of price changes. By utilizing this model, a person is able to make better informed purchase and selling decisions related to Bitcoin and Ethereum. This paper gives basic knowledge on how sentimental analysis on twitter can be applied but it only covers information on bitcoin and etherium.

Michael Ettredge, John Gerdes, and Gilbert Karuga- CNN Based Bitcoin trend analysis [10]:Using historical data of bitcoin from different API built the model that analyses the trend. Here the author collected historical price across several web bitcoin price database which are processed to collect the price of every days closing price.From the extracted data they used cnn algorithm to find the trend hidden across the day of the week. The high low prediction etc. Here the pooling layer loses lots of valuable information.

2.2 **Drawbacks of Existing System**

- There is no existing system that would work on the idea of analyzing tweets to predict trends.
- There are systems that predict the movement using social media interactions but are limited to popular cryptocurrencies such as BTC and ETH.
- Most of the existing systems are not available for free and are not well maintained (High False Positive rate and hence low accuracy).

2.3 **Problem Statement**

"To analyse and predict the trends of various crypto-currencies using live Twitter API data and deep learning techniques(LSTM)."

2.4 **Proposed System**

To develop an application that,

- Will detect the sentiment of a tweet using Natural Language Processing Toolkit.
- Analyse the trend of a crypto using a LSTM model.
- Work for various crypto currencies and not restricted to a few.
- Produces detailed report of the trend both visually and statistically

CHAPTER 3

REQUIREMENT ENGINEERING

3.1 Software and Hardware Tools Used

3.1.1 **Software Requirements**

Python

HTMl, CSS JavaScript

Flask

3.1.2 **Hardware Requirements**

Processor: Pentium 4

Operating System: Linux, Windows 7 or newer

RAM: 1 GB

Disk Drive: 20 GB

3.2 Conceptual / Analysis Modelling

3.2.1 Use case diagram

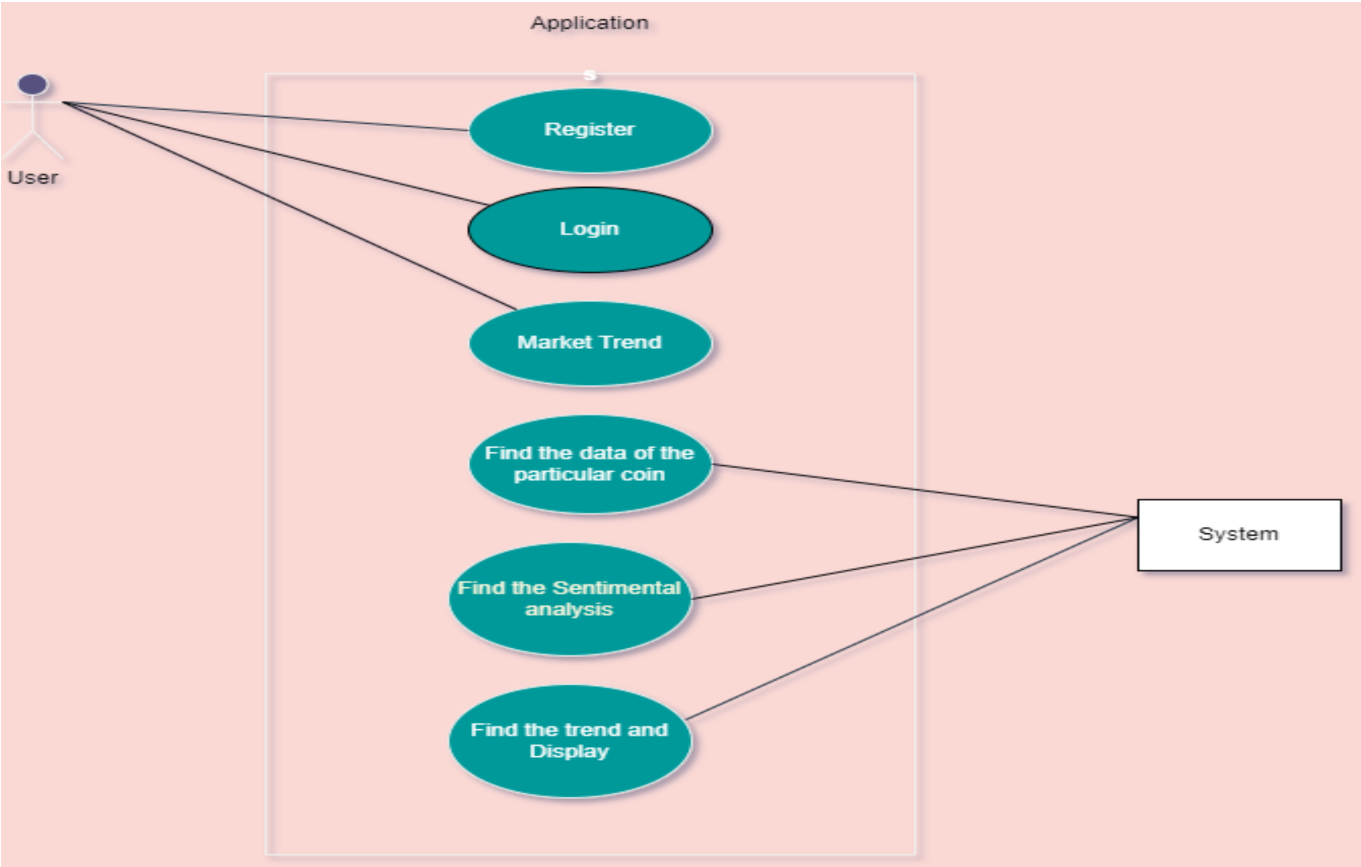

Figure 1: Use case diagram for web-based Twitter Trend Analysis System

A use case diagram is a graphic depiction of the interactions among the elements of a system. A use case is a methodology used in system analysis to identify, clarity, and organize system requirements. Diagrammatic representation is what user can view through application when he/she opens the application, and if the user is an admin, he/she can login using email-id and password. After authentication of successful details, the user able to view the all the information regarding the preferred crypto currency.

3.2.2 **Sequence Diagram**

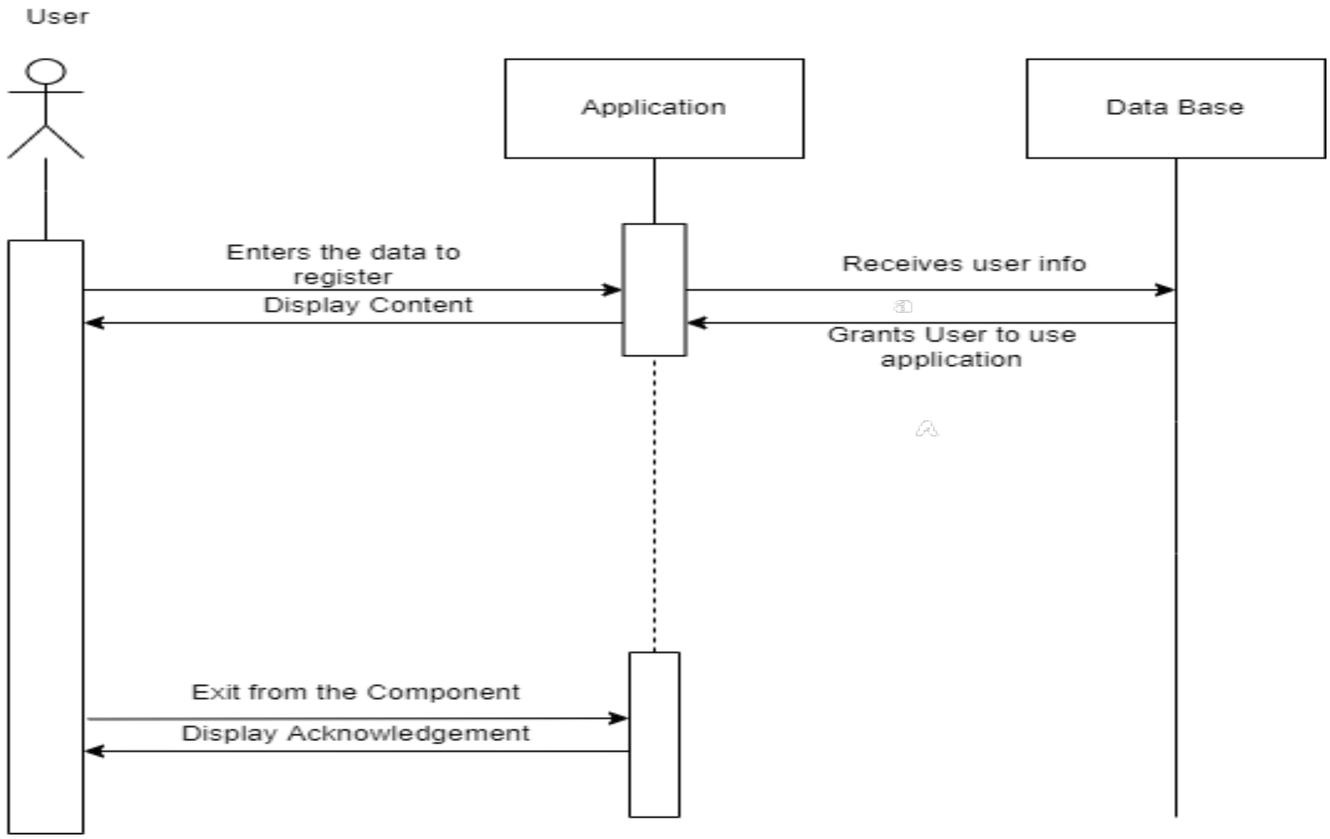

Figure 2: Sequence diagram of User Registration for a web-based Twitter Trend Analysis System

A sequence diagram is an interaction diagram that shows how processes operate with one another and in what order. It is a construct of a message sequence chart. A sequence diagram shows object interactions arranged in time sequence. It depicts the objects and classes involved in scenario and the sequence of messages exchanged between the objects needed to carry out the functionality of the scenario.

The Figure 2 shows the interaction between the user and the application while registerarring an account in the web applications.When the user enters a data applications verifies and stores in the database.From which if user tries to login next time it will verify.

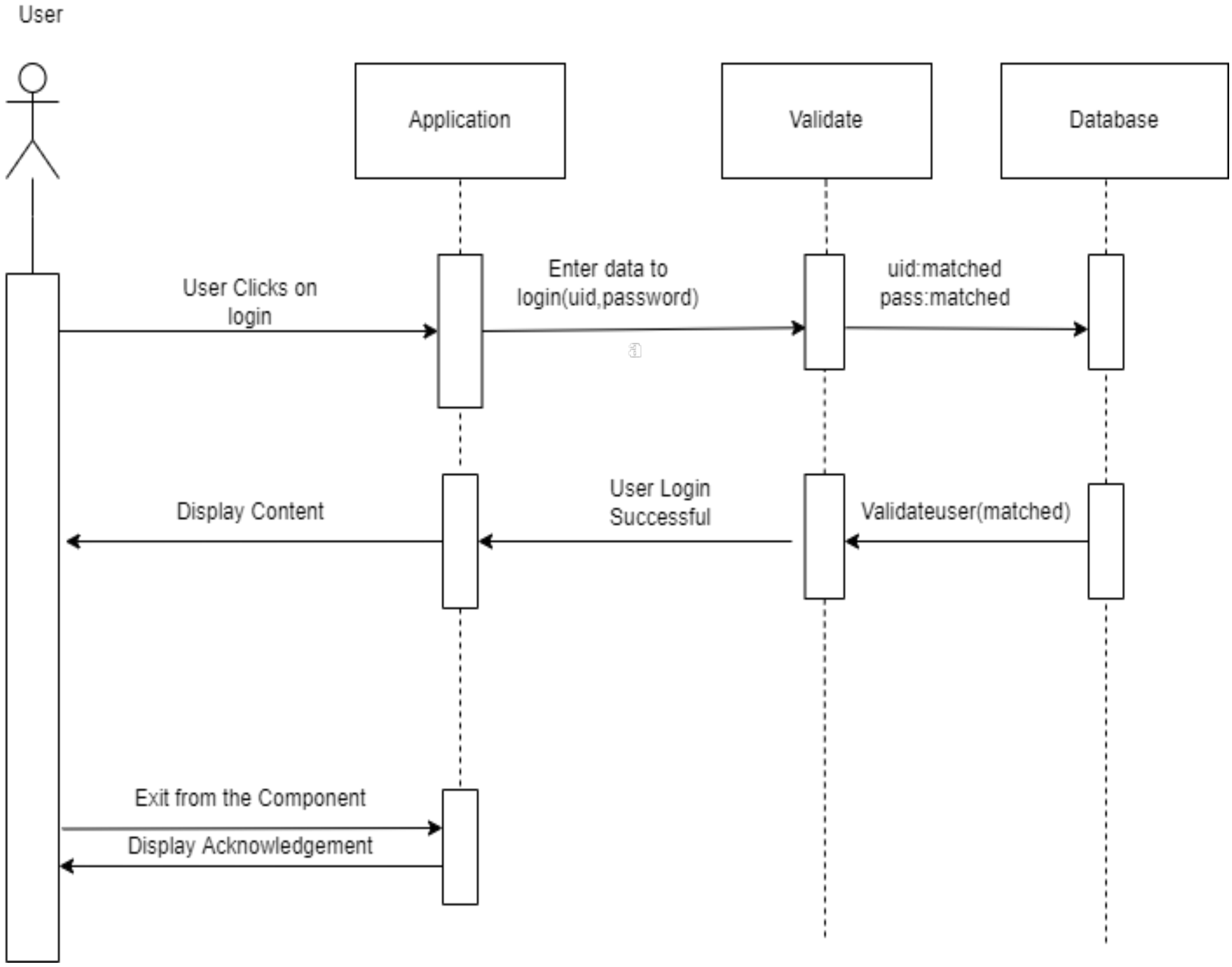

Figure 3: Sequence diagram of User Login for a web-based Twitter Trend Analysis System

The above figures dispalys how the user and system interacts when the user tries to login to the system.When the user already created an account. He now can enter the required data which he used while creating the account .the app takes the data verifies with the data which is present in the system if it matches then lets user to use the app otherwise user has to re enter correct.

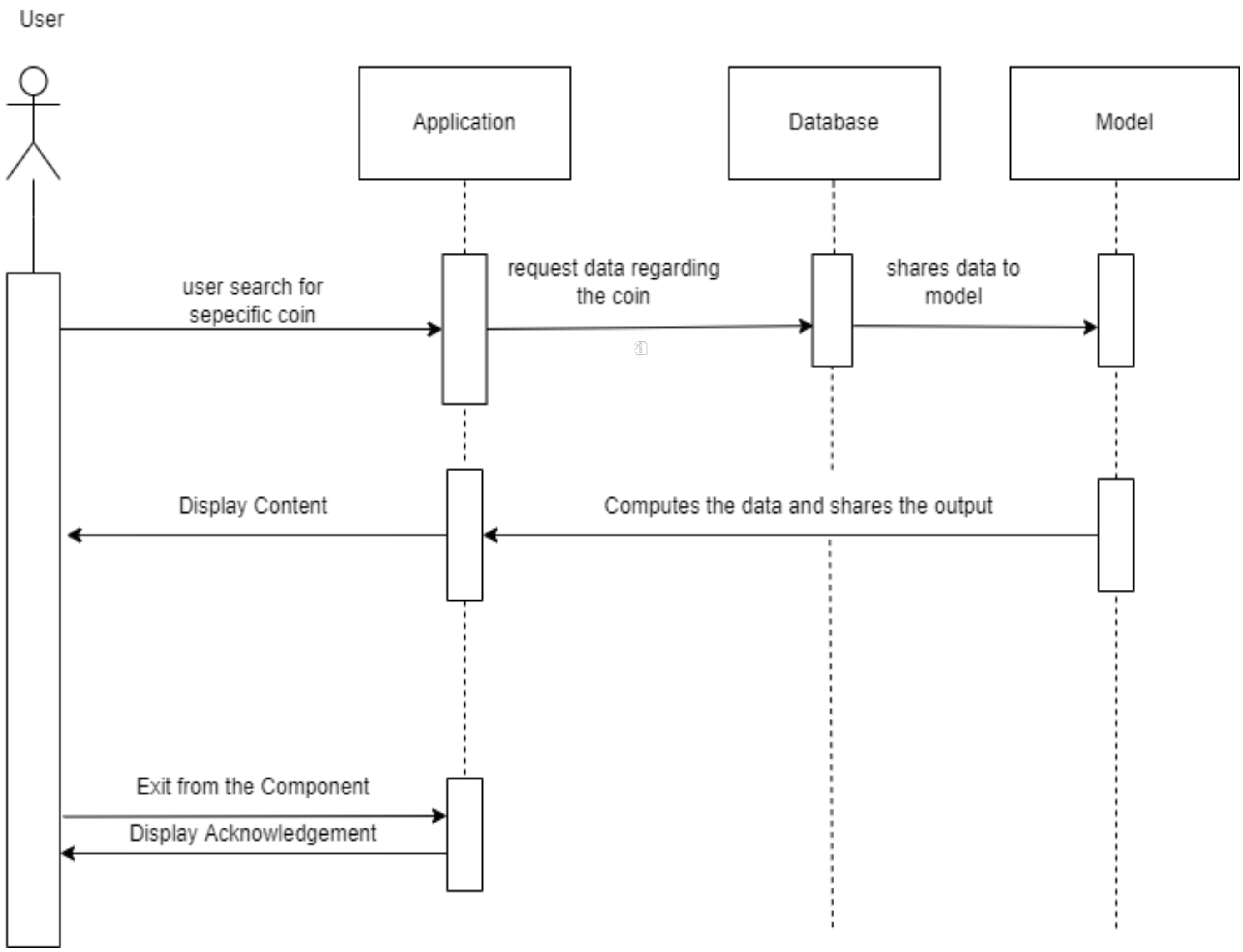

Figure 4: Sequence diagram for Market Trend

In the above sequence diagram we can observe that after successful login the user gets to mainframe where the contents are available when user procceds to check information regarding specific coin the app shares info to db which proceeds to give the training data with respect to training data the model predicts the value which is in json object format and the front end app displays the

3.2.3 **Class diagram**

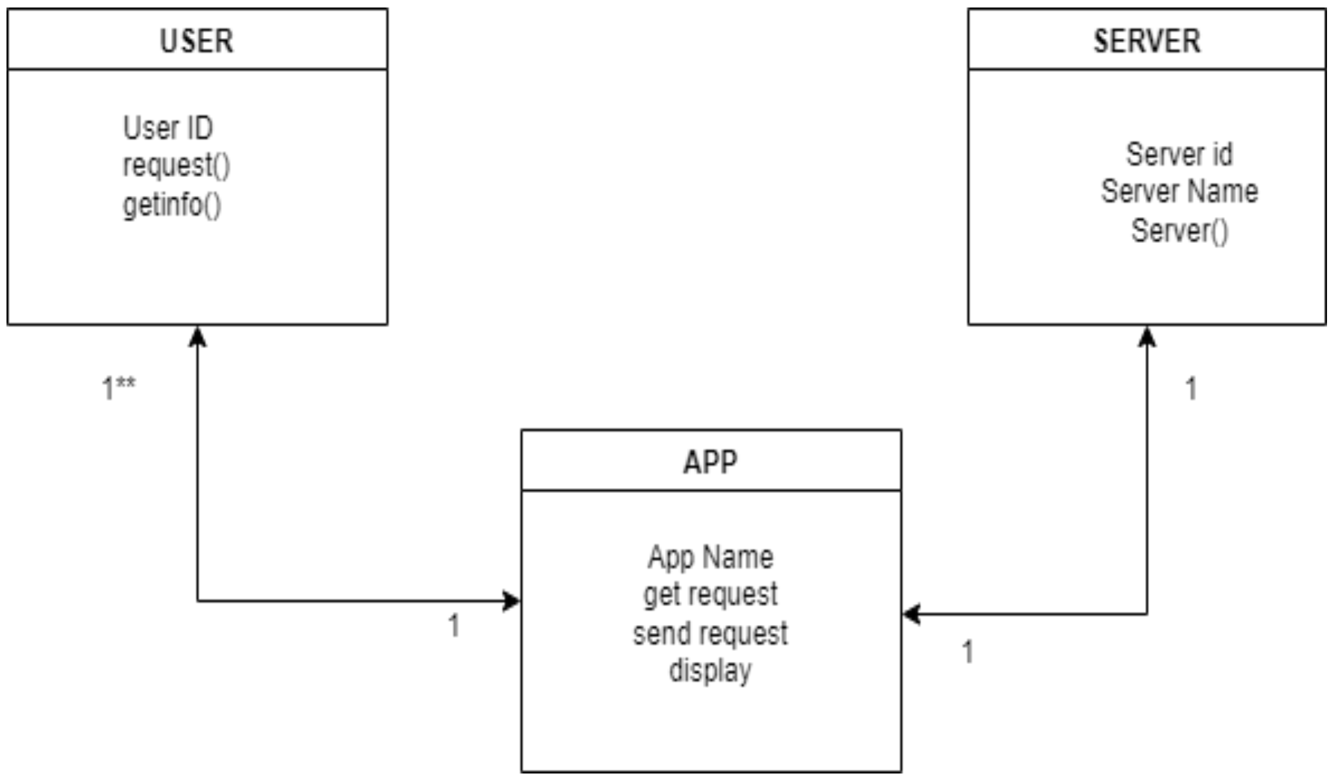

Figure 5: Class diagram for a web-based Twitter Trend Analysis System

Class diagram describes the structure of the system by showing the systems classes, their attributes, operations and the relationship among objects.

The purpose of Figure 5 is to model the static view of an application by using Class diagram are the only diagrams which can be directly mapped with object-oriented languages and thus widely used at the time of construction.

User table contains userID, a userID serves two purposes, it can request to access the application and can also get the information of a particular cryptocurrency. These can be achieved through the application. In app it takes the user request and validates through server, if the information is present then it grants access for user to check the trends of the coins which was requested.

3.2.4 **State Chart Diagram**

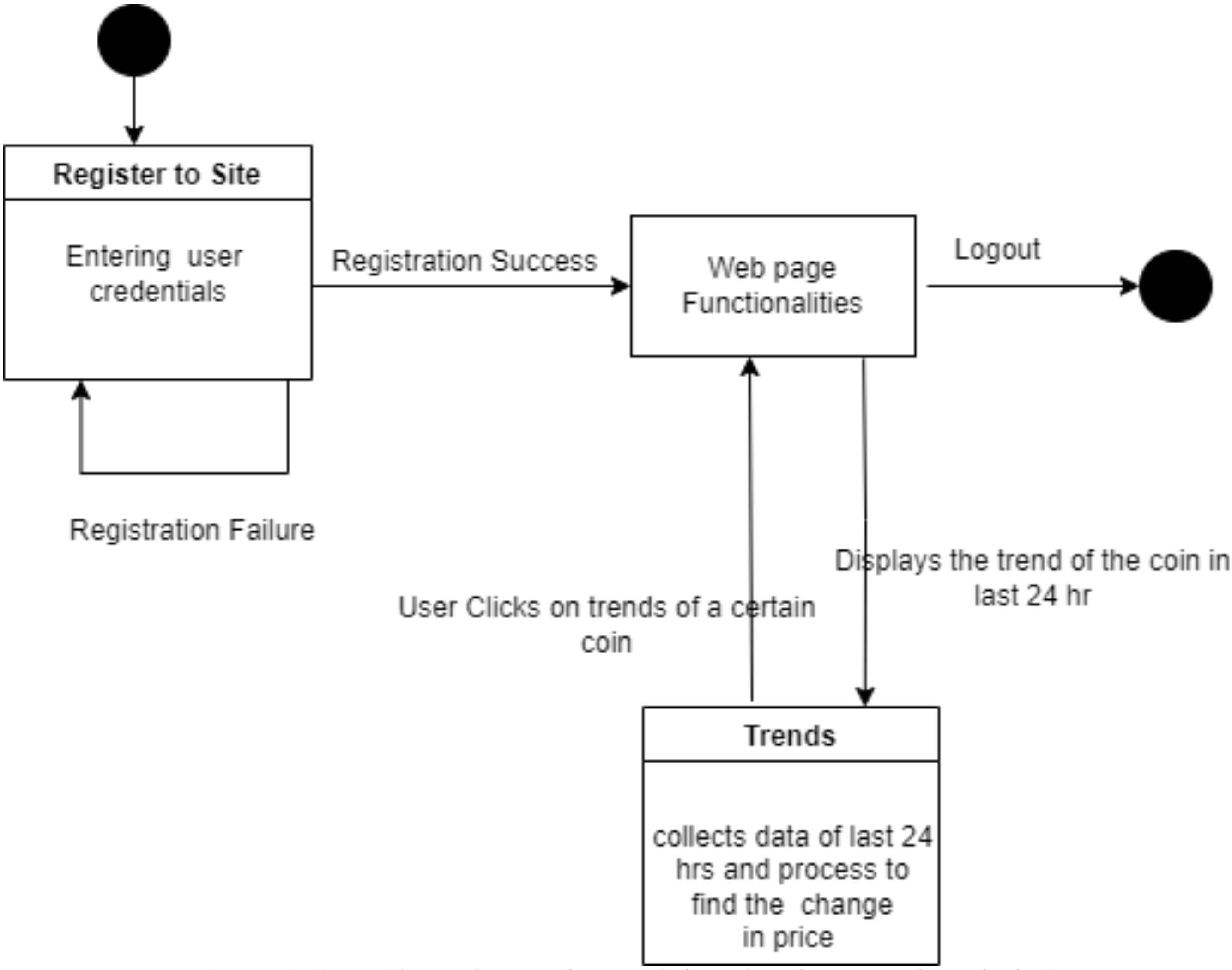

Figure 6: State Chart Diagram for a web-based Twitter Trend Analysis System

A State chart diagram describes the flow of control from one state to another state. States are defined as a condition in which an object exists and it changes when some event is triggered. The most important purpose of State chart diagram is to model lifetime of an object from creation to termination. Here when a user register to site it will register only when the user fulfills the requqirements.After registering successfully the user can use the web page functionalities where he can check the trend of each crypto currencies.

3.2.5 **Activity Diagram**

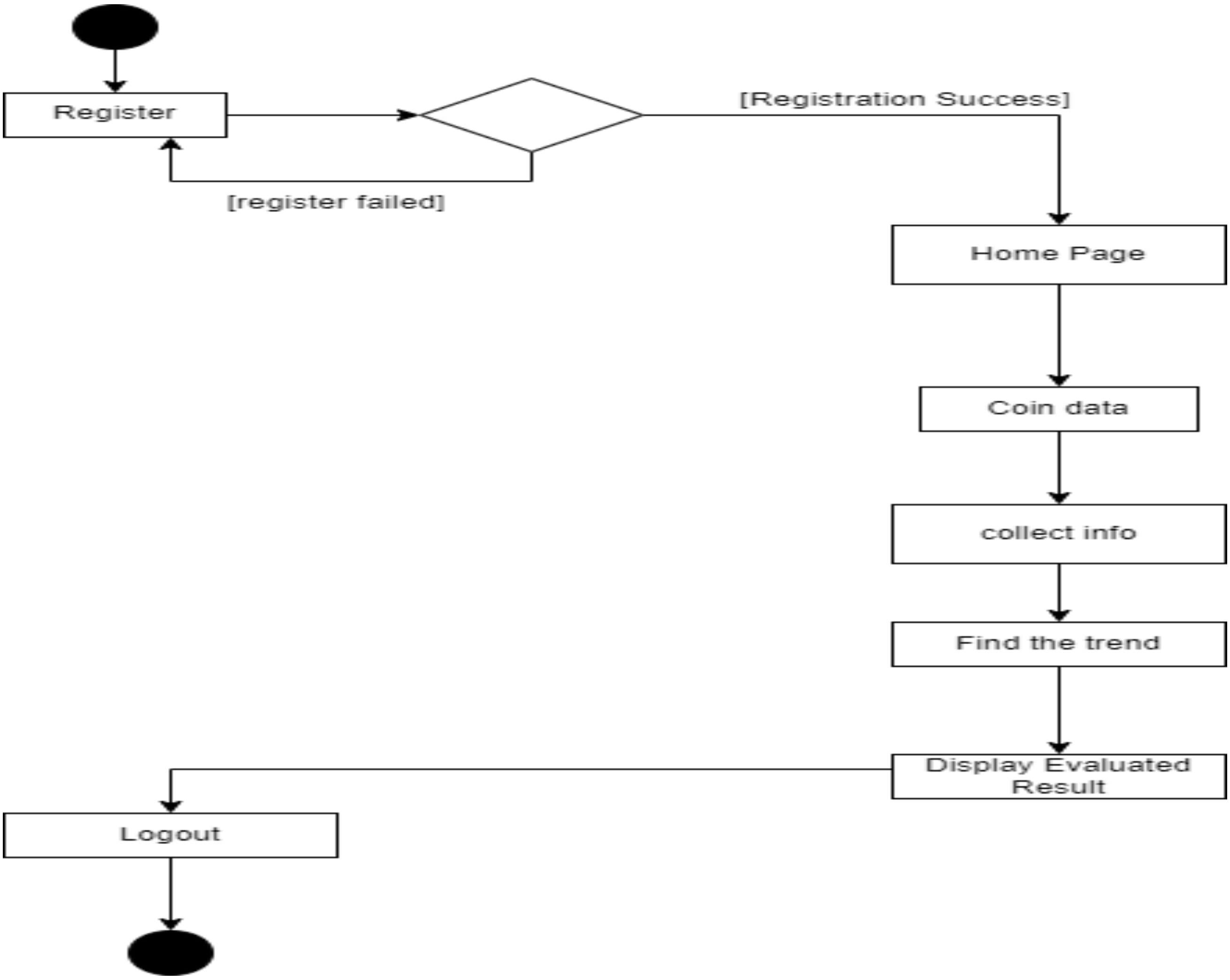

Figure 7: Activity diagram for a web-based Twitter Trend

Activity diagrams are graphical representations of workflows of stepwise activities with support for choice, iteration and concurrency. In the Unified Modeling Language, activity diagrams are intended to model both computational and organizational processes. Above Figure visually presents a series of actions or flow of control in a system taking place between the user and the system portrays the control flow from a start point to a finish point showing the various decision paths that exist while the activity is being executed. We can also depict both sequential processing and concurrent processing of activities using an activity diagram.

3.3 Software Requirements Specification

Functional Requirements

Account Creation: Users and traders who wish to look at the trends can register and create an account.

UI/UX: Provides an intuitive interface for traders to observe and interact with a cryptocurrency. The charts and comparison of the cryptos would be done only on the latest market data.

Subscription: The user can subscribe for a particular crypto and can get charts and comparison , which would be done only on the latest data stock market data.

Historic Data: The tweets of each day for the past n number of days would be stored in the database, using which the trend of a currency on any particular day can be obtained.

Voting: The user can also be recommended on the basis of the trending crypto which would require the data regarding the cryptos.

Non-Functional Requirements

Usability: It defines the user interface of the software in terms of simplicity of understanding the user interface of crypto trend prediction software, for any kind of crypto trader and other stakeholders in crypto market.

Efficiency: maintaining the possible highest accuracy in the crypto trends in shortest time with available data.

Performance: It is a quality attribute of the crypto trend prediction software that describes the responsiveness to various user interactions with it.

Scalability: It provides highly accurate trend detection which can be further scaled up to different, both small and big crypto currencies and communities.

CHAPTER 4

PROJECT PLANNING

4.1 Project Planning and Scheduling

PROJECT TITLE	CRYPTO TREND ANALYSIS	COLLEGE NAME	Bangalore Institute of Technology
PROJECT ID	18P51		

SERIAL NUMBER	TASK TITLE	ESTIMATED TIME(h)	HOURS SPENT (h)	PERCENTAGE OF TASK COMPLETED(%)	2021				2022					
					Sept	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun
1	**Project Idea Development**													
1.1	Initial Research for Project Idea	32	32	100										
1.2	Project Idea Development	36	36	100										
2	**Project Related Research, Analysis and Planning**													
2.1	Research	24	24	100										
2.2	Information Gathering	34	36	100										
2.3	Planning and Requirement Analysis	20	20	100										
2.4	Requirements Specification	16	16	100										
2.5	Preliminary Presentation	20	0	0										
3	**Future Plan**													
3.1	Design Analysis/Algorithm Design	80	0	0										
3.2	Module Implementation	400	0	0										
3.3	Testing Phase	250	0	0										
3.4	Result Analysis	140	0	0										
3.5	Report Generation/Final Submission	81	0	0										

Figure 8: Gantt chart for project planning

CHAPTER 5

SYSTEM DESIGN

5.1 System Architecture

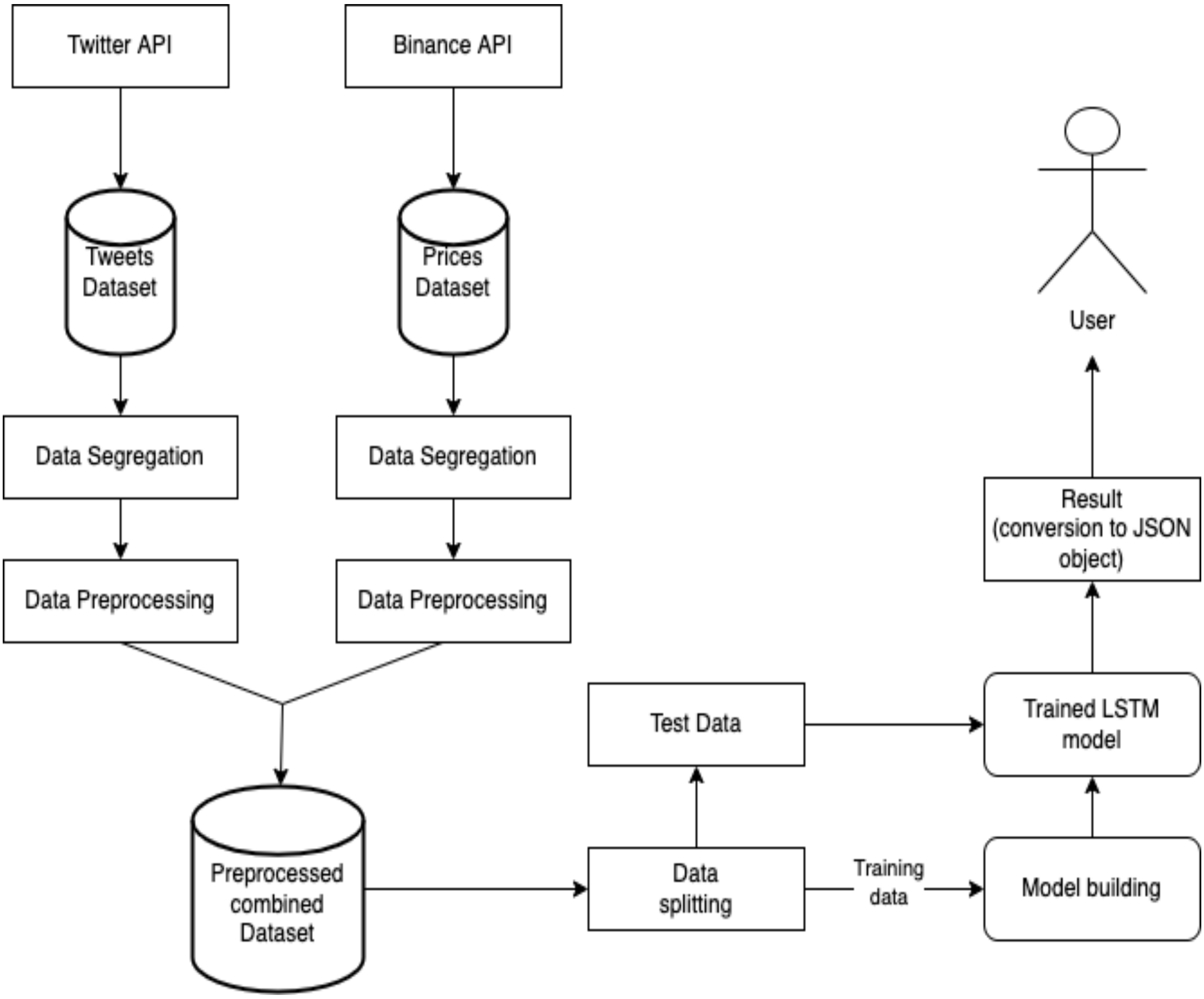

Figure 9: System Architecture of Bitcoin prediction

5.2 Component Design / Module Decomposition

Dataset collection (Twitter): In this module , we collect the tweets data from the Twitter API and crypto prices using the data available from Binance API. The dataset contains all the tweets which are available along with their timestamp.

Data Pre-Processing: Preprocessing data(twitter) is a common first step the deep learning workflow to prepare raw data in a format that the network can accept. Here we mainly use to cleanse each i.e. to remove hashtags , urls, emojis.

Data Pre-processing (Binance): In this module, we pre-process crypto data ,i.e. manipulating and casting the strings(data-time) of crypto coins dataframe to timestamps.

Joining datasets: In this module, we join both sentimental score and the price data on the basis of date time.
Feature extraction: The process of transforming raw data into numerical features that can be processed while preserving information in the original set.

Data Splitting: This model is commonly used in deep learning to split data into a train and test set. This approach allows us to find the model hyper-parameter and also estimate the generalization performance.

Model training : In this models are trained by using large sets of labeled data and neural network architectures that contains all the feature we extracted.

Performance Evaluation: In this module, we evaluate the performance of trained deep learning model using performance evaluation criteria such as root mean square.

Prediction of price: In this module we use trained and optimized deep learning model to predict the trend of selected crypto price

5.3 Interface Design

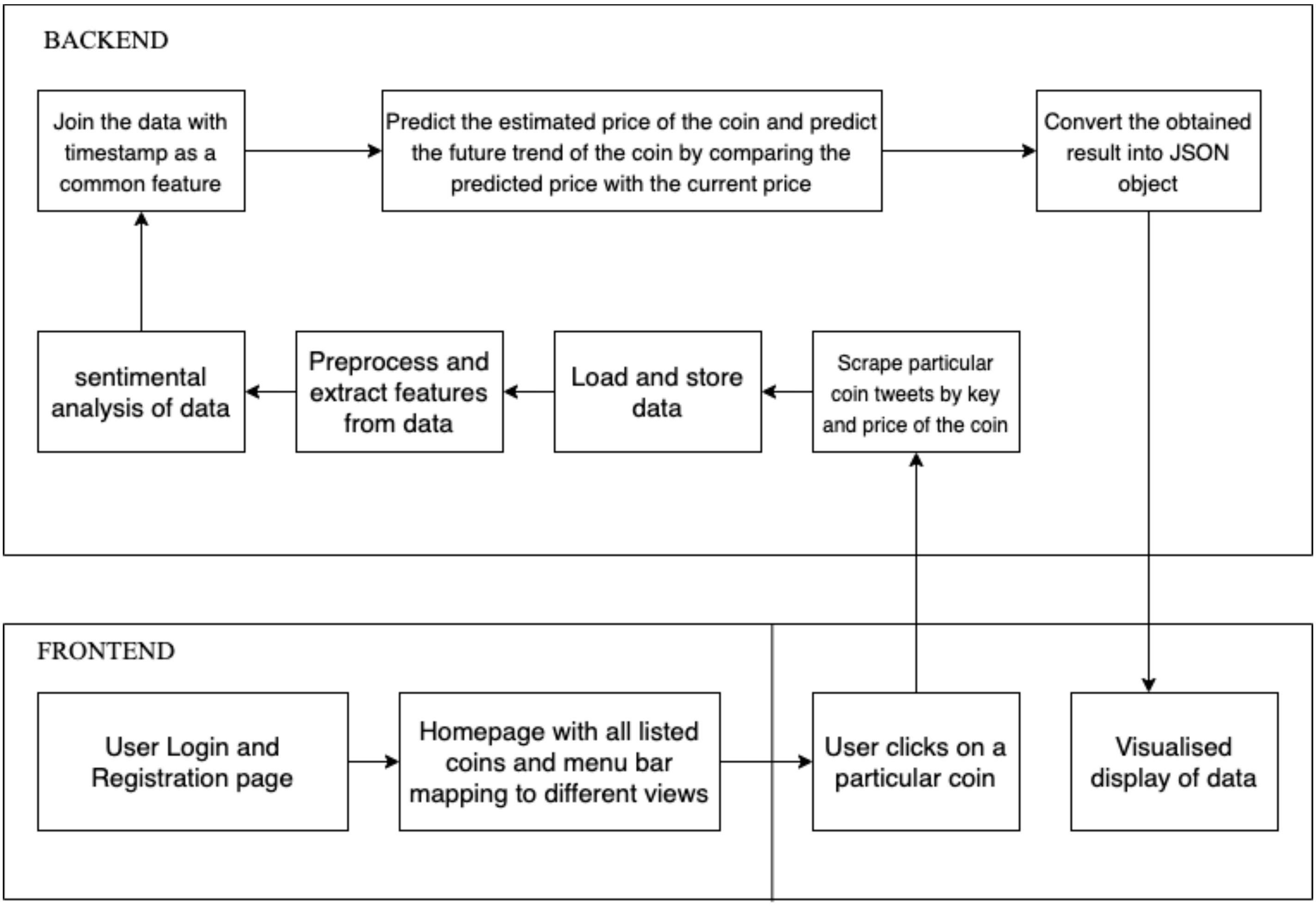

Figure 10: Interface Design for proposed system

5.4 Data Structure Design

Array : Array is a data structure consisting of a collection of elements, each identified by at least one array index or key. Array is used to store the predicted values of trained model to evaluate performance.

List : Lists are used to store multiple items in a single variable. This is used in multi-levels in the program for different use.

DataFrame : Data Frame is a collection of series where each series represents a record in the dataset.

JSON : It is a lightweight data interchange format. It is easy for humans to read and write. It is also easy for machines to parse and generate.

5.5 Algorithm Design

LSTM Algorithm :

PURPOSE: Prediction of price of the crypto coin.

INPUT: selecting the coin that we need to predicting.

OUTPUT: Visualizing the future trends of required crypto currency**.**

Step 1: Choose a Dataset

Step 2: Prepare Dataset for Training

Step 3: Create Training Data in an array that contain sentimental score and price

Step 4: Assigning Labels and Features

Step 5: Split it to 3d form for use in LSTM

Step 6: Define, compile and train the LSTM model

Step 7: make prediction ,compute error and find the future price

CHAPTER 6

IMPLEMENTATION

6.1 Implementation Approaches

```
api = tweepy.API(auth)

try:
    os.remove('result.csv')
    #print "File deleted"
except:
    #print "File was not present already"
    pass
csvFile = open('result.csv', 'w')
#Use csv writer
csvWriter = csv.writer(csvFile)
#Query(q) ---> AND (surge OR crash OR plunge OR high OR low OR future OR amazin
data = tweepy.Cursor(api.search,q = "bitcoin",since = "2017-11-06",until = "201
#most recent data is fetched first
while True:
    try:
        tweet = data.next()
        if tweet.user.followers_count > 0: #collecting tweets made by users wit
            #i+=1
            # Write a row to the CSV file. I use encode UTF-8
            csvWriter.writerow([tweet.user.name.encode('utf-8', errors='ignore'
            #print("------wrote a tweet-----")
    except tweepy.TweepError:
        #print("---------------------In sleep In sleep In sleep In sleep-------
        time.sleep(600)
        continue
    except StopIteration:
        #print("---------------------Something is wrong-----------------------
        break
csvFile.close()
```

```
[ ]:
from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer
analyser = SentimentIntensityAnalyzer()
def senti_score_udf(sentence):
    snt = analyser.polarity_scores(sentence)
    return ([snt['neg'], snt['neu'], snt['pos'], snt['compound']])
func_udf2 = udf(senti_score_udf, ArrayType(FloatType()))
CleanDF = CleanDF.withColumn('p_neg', func_udf2(CleanDF['CleanedTweets'])[0])
CleanDF = CleanDF.withColumn('p_neu', func_udf2(CleanDF['CleanedTweets'])[1])
CleanDF = CleanDF.withColumn('p_pos', func_udf2(CleanDF['CleanedTweets'])[2])
CleanDF = CleanDF.withColumn('p_comp', func_udf2(CleanDF['CleanedTweets'])[3])
CleanDF.show(3)
```

```
+--------------------+--------------------+--------------------+-----+-----+-----+-------+
|            DateTime|               Tweet|       CleanedTweets|p_neg|p_neu|p_pos| p_comp|
+--------------------+--------------------+--------------------+-----+-----+-----+-------+
|Thu Nov 09 17:43:...|RT @Forbes: The F...|The Failure of Se...|0.204|0.617|0.179|-0.1027|
|Thu Nov 09 17:43:...|RT @mindstatex: L...|Lots of love from...|  0.0| 0.56| 0.44|  0.875|
|Thu Nov 09 17:43:...|RT @FernandoHuama...|Warning Built in ...| 0.13| 0.87|  0.0|  -0.34|
+--------------------+--------------------+--------------------+-----+-----+-----+-------+
```

```
# design network
model = Sequential()
model.add(LSTM(5, input_shape=(train_X.shape[1], train_X.shape[2])))
model.add(Dense(1))
model.compile(loss='mae', optimizer='adam')
# fit network
history = model.fit(train_X, train_y, epochs=20, batch_size=4, validation_data=(test_X, test_y), verbose=2, shuffle=Fa
# plot history
```

```
Train on 170 samples, validate on 38 samples
Epoch 1/20
 - 1s - loss: 0.0688 - val_loss: 0.1399
Epoch 2/20
 - 0s - loss: 0.0660 - val_loss: 0.1376
```

6.2 **Coding Details and Code Efficiency**

With the use of above code we manage to extract the tweets of given time frame tweepy library lets us to extract the tweets from the user having more than one follower so we can ignore all bot accounts After we cleanse the data with the help of vader sentimental analyzer, we find the sentimental score and get the positive score, negative score an neutral score.

After splitting the data into train and test we design the LSTM model for the multiple features we extracted in the process and the model we designed we plot the data for historical data with respect to data which model predicted we used many weak learners to build the model to predict sentiment score such as logistic regression has an accuracy of 56% , Random Forest with 82%, Multinomial naïve bayes with 78%. Our timeseries regression model got mean absolute error of 0014157085308444484

CHAPTER 7

TESTING

7.1 **Testing Approaches**

7.1.1 **Unit testing**

Test Case 1:

Data-extraction: This module is used to scrape data of tweets and historical data

Test	Test Data	Expected-result	Actual result	Pass/Fail
1	Not mentioning time	no data extracted	no data extracted	pass
2	Extracted for year at single runtime	results the tweet/price for the given timeframe	runtime error	fail
3	Time frame for couple of weeks and less data limit	results the tweet/price for the given time	results the tweet/ price given time	pass

Test Case 2:

Sentiment_analysis: This module is used to for sentiment analysis for given tweets

Test	Test Data	Expected-result	Actual result	Pass/Fail
1	Tweets	sentiment score for the given tweets	sentiment score for the given tweets	pass

Test Case 3:

Model-price-prediction: this module is used to price prediction and trend analysis

Test	Test Data	Expected-result	Actual result	Pass/Fail
1	test-data	prediction of price	prediction of price	pass

	for the test data	for the test date	for the test data	

7.1.2 **Integrated manual testing**

Test case1:

Home-page(): This function will lead to home page of the website

Test	Test Data	Expected-result	Actual result	Pass/Fail
1	No test data	the website should lead to home_page.html	the website lead to home_page.html	pass

Test case2:

Bitcoin_page():this function leads to bitcoin page which contain price prediction of bitcoin on daily and weekly basis

Test	Test Data	Expected-result	Actual result	Pass/Fail
1	Not mentioning Time	It should tell user to mention time period to check	server error	fail
2	Selecting daily/ Weekly	graphical output of future price	graphical output future price	pass

Test case3:

litecoin_page():this function leads to Litecoin page which contain price prediction of bitcoin on daily and weekly basis

Test	Test Data	Expected-result	Actual result	Pass/Fail
1	Not mentioning Time	It should tell user to mention time period to check	server error	fail
2	Selecting daily/	graphical output of	graphical output	pass

	Weekly	future price	future price	

Test case4:

Sentiment():this function leads to real-time sentiment analysis of the input coin

Test	Test Data	Expected-result	Actual result	Pass/Fail
1	Selecting required Coins prediction	sentiment analysis of last 100 tweets	sentiment analysis of last 100 tweets	pass
2	Manual tweet Sentiment analysis	sentiment score of given tweet	sentiment score of given tweet	pass

CHAPTER 8:

RESULTS DISCUSSION

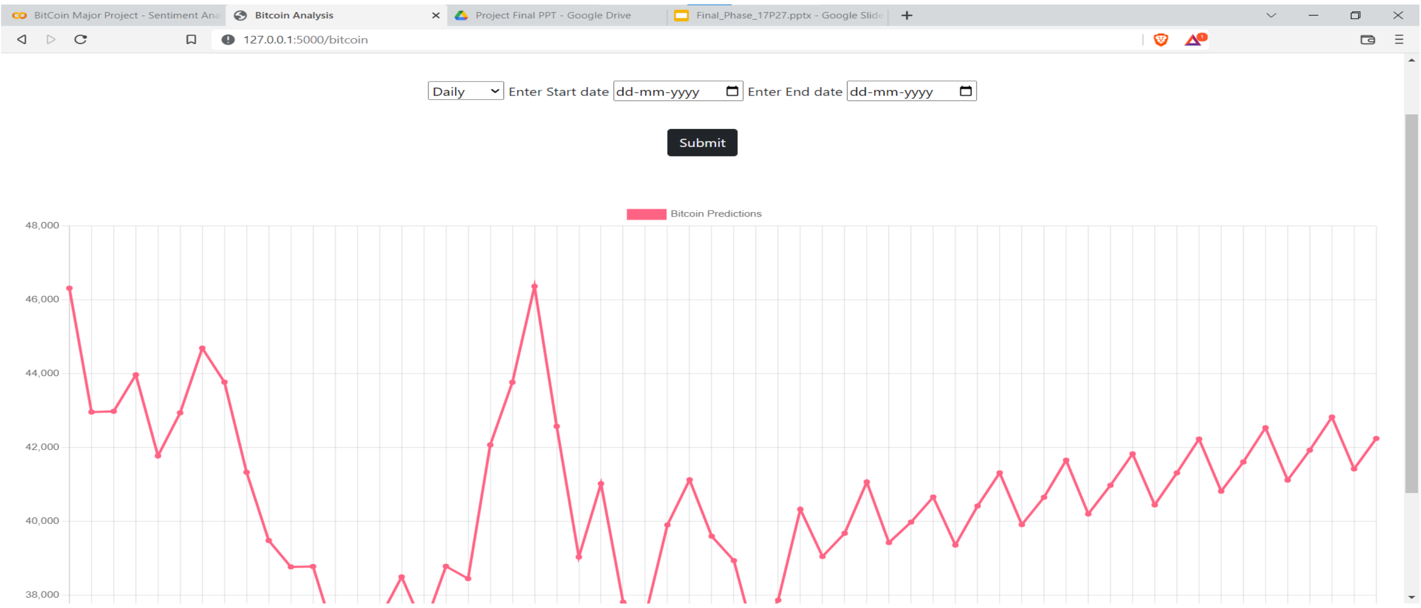

Fig 11 : Bitcoin prediction daily

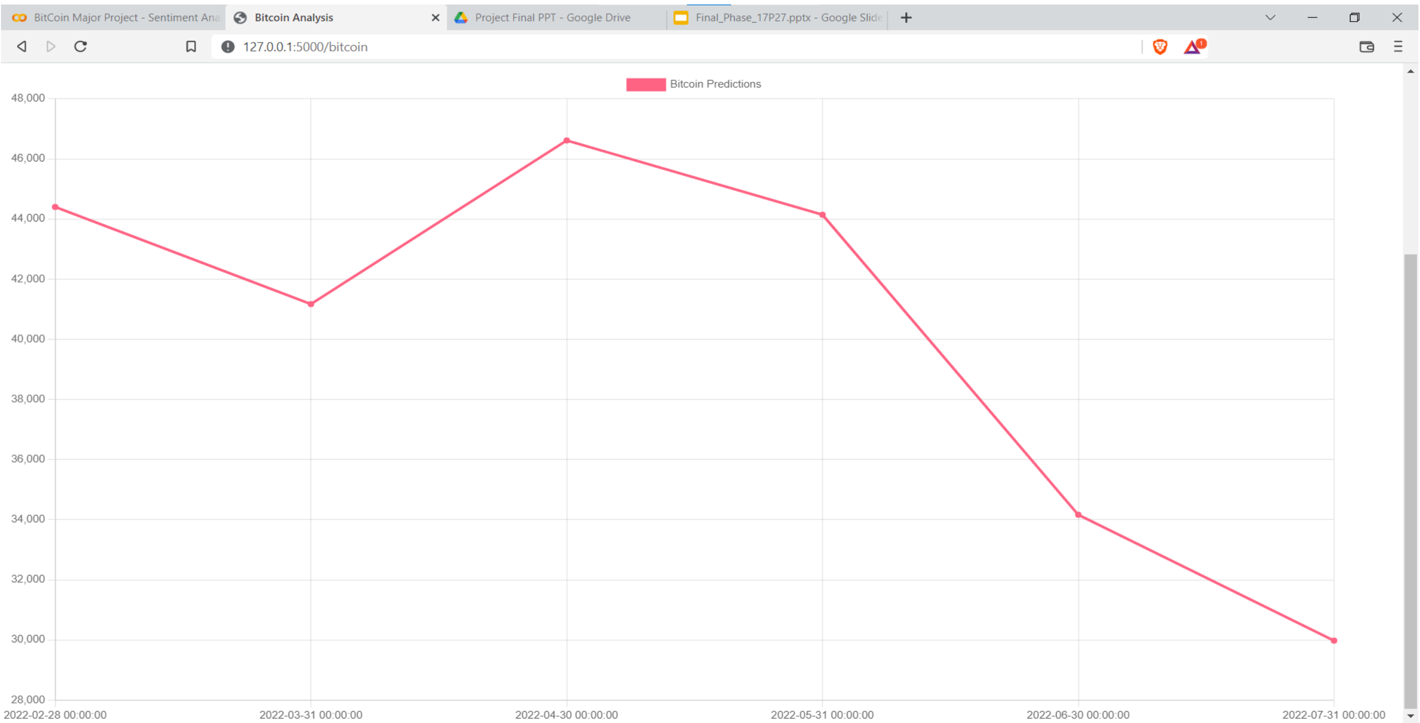

Fig 12 : Bitcoin prediction monthly

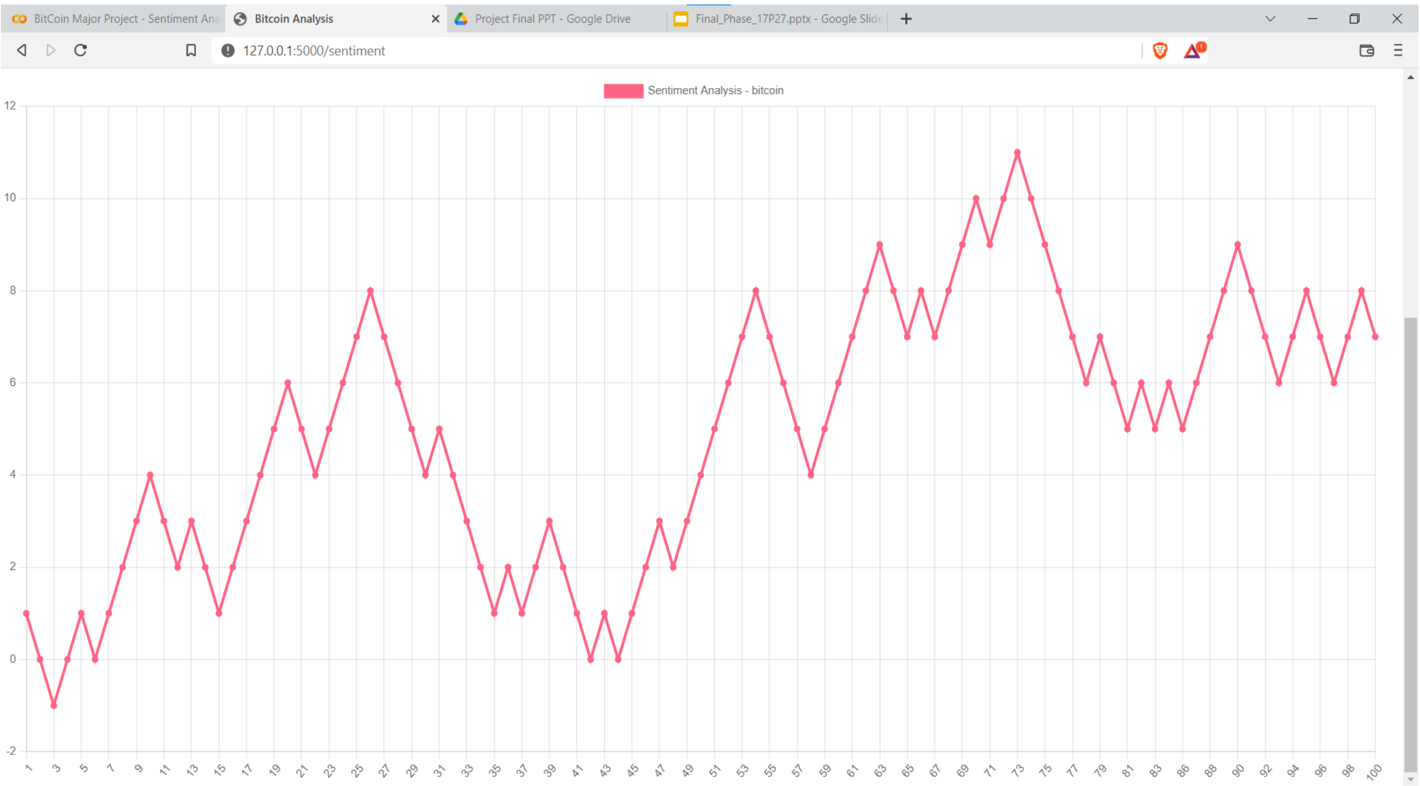

Fig 13 : Real time twitter sentiment analysis

Chapter 9

CONCLUSION, APPLICATIONS AND FUTURE WORK

9.1 **Conclusion**

Now a days cryptocurrency is considered one of the most riskiest and profitable investment which can give immense profit at very short time.

A tweet by any giant influencer plays a major role in designing the trends of crypto currency.

Getting the live data from the twitter is not alone sufficient as it has to be pre-processed for the meaning full data.

These statistic data obtained then plays a very important decision factor for buying, holding or selling the particular crypto. Hence reduces the risk of investment.

9.2 **Application**

An intelligent system to get live info of the trending crypto-currency.

It helps in extracting the meaningful data from the processed tweets.

It can help in making buy, sell or hold decision for the user before the crypto prices go bullish or bearish.

It's a Web based application hence can be accessed from any part of the world at any given time.

The main application will be to predict the impact of the social media namely twitter on crypto

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