GOVERNMENT POLYTECHNIC, PUNE

(An Autonomous Institute of Government of Maharashtra)

DEPARTMENT OF COMPUTER ENGINEERING

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PROJECT REPORT ON

"Fake News Detection"

SUBMITTED BY

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Enrolment Number : 1706060

UNDER THE GUIDENCE

OF

Prof. T. P. Sharma

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GOVERNMENT POLYTECHNIC, PUNE

(An Autonomous Institute of Government of Maharashtra)

CERTIFICATE

This is to certify that **Shivani Vidhyadhar Kulkarni** of class Third Year (2019-2020) have successfully completed project on **“Fake News Detection”** under the guidance of **“Mr.T.P.Sharma”** in parallel fulfillment of the requirement for the award of Diploma in Computer Engineering from Government Polytechnic, Pune.

Mr.T.P.Sharma	**Mr.U.V.Kokate**	**Dr.V.S Bandal**
(Project Guide)	(H.O.D)	(Principal)

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ABSTRACT

Sentiment analysis deals with identifying and classifying opinions or sentiments expressed in source text. Social media is generating a vast amount of sentiment rich data in the form of tweets, status updates, blog posts etc. Sentiment analysis of this user generated data is very useful in knowing the opinion of the crowd. Twitter sentiment analysis is difficult compared to general sentiment analysis due to the presence of slang words and misspellings. Knowledge base approach and Machine learning approach are the two strategies used for analyzing sentiments from the text. Public and private opinion about a wide variety of subjects are expressed and spread continually via numerous social media. Twitter is one of the social media that is gaining popularity. Twitter offers organizations a fast and effective way to analyze customers' perspectives toward the critical to success in the market place. Developing a program for sentiment analysis is an approach to be used to computationally measure customers' perceptions. This project uses knowledge base including various patterns for tweets along with multiple strategies to detect the sentiment expressed in a tweet and if a tweet is genuine or not. Various machine learning and knowledge base approaches are used to compare patterns and apply strategies and NLP for sentiment analysis.

Keywords: NLP(Natural Language Processing), Sentiment analysis, machine learning, influence of tweets, POS(Part of Speech)

1.INTRODUCTION

Twitter has emerged as a major micro-blogging website, having over 100 million users generating over 500 million tweets every day. With such large audience, Twitter has consistently attracted users to convey their opinions and perspective about any issue, brand, company or any other topic of interest. Due to this reason, Twitter is used as an informative source by many organizations, institutions and companies. On Twitter, users are allowed to share their opinions in the form of tweets, using only 140 characters. This leads to people compacting their statements by using slang, abbreviations, emoticons, short forms etc. Along with this, people convey their opinions by using sarcasm and polysemy. Hence it is justified to term the Twitter language as unstructured. In order to extract sentiment from tweets, sentiment analysis is used. The results from this can be used in many areas like analyzing and monitoring changes of sentiment with an event, sentiments regarding a particular brand or release of a particular product, analyzing public view of government policies etc.

A lot of research has been done on Twitter data in order to classify the tweets and analyze the results. In this project we aim to predict the sentiments from tweets by checking the polarity of tweets as positive, negative or irrelevant. Sentiment analysis is a process of deriving sentiment of a particular statement or sentence. It’s a classification technique which derives opinion from the tweets and formulates a sentiment and on the basis of which, sentiment classification is performed. Sentiments are subjective to the topic of interest. We are required to formulate that what kind of features will decide for the sentiment it embodies. In the programming model, sentiment we refer to, is class of entities that the person performing sentiment analysis wants to find in the tweets. Whereas machine learning approach involves use of feature extraction and training the model using feature set and some dataset. The basic steps for performing sentiment analysis includes data collection, pre-processing of data, feature extraction, selecting baseline features, sentiment detection and performing classification either using simple computation or else machine learning approaches. Features are like Parts-of speech features i.e. nouns, adverbs, adjectives, etc. in each tweets are tagged.

We for the accuracy purpose of polarity will be detecting sentiments along with various knowledge base patterns and multiple machine learning strategies to evaluate the sentiments. Alongside we will be checking if the tweet is genuine or not or if has influenced by other tweets which can be very useful in fake tweets mitigation on social medias. This approach will produce the higher accuracy for polarity by considering POS factor and genuineness as well as can be used in various sectors such as analyzing product reviews or government policies, etc. where it can be found if negative influence is spread and if it affects people.

1.1 Background

Sentiment analysis caught attention as one of the most active research areas with the explosion of social networks. The enormous user-generated content resulting from these social media contained valuable information in the form of reviews, opinions, etc about products, events and people. Most sentiment analysis studies use machine learning approaches, which require large amount of user generated content for training. The research on sentiment analysis so far has mainly focused on two things: identifying whether a given textual entity is subjective or objective, and identifying polarity of subjective texts. In the following sections, we review literature on both general and twitter-specific sentiment analysis in brief. Starting with general sentiment analysis, we also discuss about the issues in sentiment analysis that make it a difficult task than other text classification tasks. Later on, we move to the focus area of this thesis, i.e. twitter specific approaches. In a study, present a comprehensive review of the literature written before 2008. Most of the material on general sentiment analysis is based on their review.

1.1.1 General Sentiment Analysis

Sentiment analysis has been carried out on a range of topics. For example, there are sentiment analysis studies for movie reviews, product reviews, and news and blogs.

1.1.2 Issues in Sentiment Analysis

Research reveals that sentiment analysis is more difficult than traditional topic- based text classification, despite the fact that the number of classes in sentiment analysis are less than the number of classes in topic-based classification. In sentiment analysis, the classes to which a piece of text is assigned are usually negative or positive. They can also be other binary classes or multi-valued classes like classification into \positive", \negative" and \neutral", but still they are less than the number of classes in topic-based classification. Sentiment analysis is tougher compared to topic-based classification as the latter relies on keywords for classification. Whereas in the case of sentiment analysis keywords a variety of features have to be taken into account. The main reason that sentiment analysis is more difficult than topic-based text classification is that topic-based classification can be done with the use of keywords while this does not work well in sentiment analysis.

Other reasons for difficulty are: sentiment can be expressed in subtle ways without any perceived use of negative words; it is difficult to determine whether a given text is objective or subjective (there is always a newline between objective and subjective texts); it is difficult to determine the opinion holder (example, is it the opinion of the author or the opinion of the commenter); there are other factors such as dependency on domain and on order of words. Other challenges of sentiment analysis are to deal with sarcasm, irony, and/or negation.

1.1.3 Classification of approaches

Sentiment analysis is formulated as a computational linguistics problem. The classification can be approached from different perspectives depending on the nature of the task at hand and perspective of the person carrying out sentiment analysis. The familiar approaches are discourse-driven, relationship-driven, language-model-driven, or keyword-driven. We discuss these approaches in the subsequent subsections.

1.1.4 Knowledge-based approach

In this approach, sentiment is calculated as the function of some keywords. The main task is the construction of sentiment discriminatory-word lexicons that indicate a Theoretical Background and Literature Review particular class such as positive class or negative class. The polarity of the words in the lexicon is determined prior to the sentiment analysis work. There are variations to how the lexicon is created.

1.1.5 Relationship-based approach

In this approach, the classification task is approached from the different relationships that may exist between features2 and components. Such relationships include relationships between discourse participants, relationships between product features. For instance, if one wants to know the sentiment of customers about a product brand, one may compute it as a function of the sentiments on different features or components of it.

1.1.6 Language models approach

In this approach, the classification is done by building n-gram language models. A gram is a token or lexicon taken into consideration for training and classification. N-gram represents a set of such chosen lexicons. Generally, in this approach frequency of n-grams are used. In traditional information retrieval and topic-oriented classification, frequency of n-grams gives better results. The frequency is converted to TF-IDF3 to take term's importance in the document to be classified. In a study, show that in the sentiment classification of movie review blog, term-presence gives better results than term frequency. They indicate that unigram presence is more suited for sentiment analysis. But later found that bi-grams and trigrams worked better than unigrams in a study of sentiment classification of product reviews.

1.1.7 Discourse structures and semantics approach

This approach, is very dominant in the applications where prior classification of classes is not possible. Text is classified when it is encountered into the best category its (in the context of its objective). Based on the similarity of semantics of words in the text, they are grouped together and tagged in to classes. For example in reviews, the overall sentiment is usually expressed at the end of the text. As a result the approach, in this case, might be discourse-driven in which the sentiment of the whole review is obtained as a function of the sentiment of the different discourse components in the review and the discourse relations that exist between them. For instance, the sentiment of a paragraph that is at the end of the review might be given more weight in the determination of the sentiment of the whole review. Semantics can be used in role identification of agents where there is a need to do so. For example \India beat Australia" is different from \Australia beat India".

1.2 Need

Before we proceed with the explanation of our algorithms for fake tweet detection and verification, we need to provide a clear definition of fake tweets. We define a fake tweet to an unverified assertion that starts from one or more sources and spreads over time from node to node in a network. On Twitter, a fake tweet is a collection of tweets, all asserting the same unverified statement (however the tweets could be, and almost assuredly, are worded differently from each other), propagating through the communications network (in this case Twitter), in a multitude of cascades. A fake tweet can end in three ways: it can be resolved as either true (factual), false (nonfactual) or remain unresolved. There are usually several fake tweets about the same topic, any number of which can be true or false. The resolution of one or more fake tweets automatically resolves all other fake tweets about the same topic. For example, take the number of perpetrators in the Boston Marathon bombings; there could be several fake tweets about this topic:

1. Only one person was responsible for this act.
2. This was the work of at least 2 or more people.
3. There are only 2 perpetrators.
4. It was at least a team of 5 that did this.

Once fake tweet number 3 was confirmed as true, it automatically resolved the other fake tweets as well. (In this case, fake tweets 1 and 4 resolved to be false and fake tweet 2 resolved to be true.) For the purposes of this thesis, we only consider fake tweets that spread on Twitter. This thesis develops models for detection and verification of fake tweets (i.e. unverified information) that propagate on Twitter. Detection of fake tweets about an event is achieved through classifying and clustering assertions made about that event. Assertions are classified through a state-of-the-art speech-act classifier for Twitter developed for this thesis.

The classifier is a logistic regression that utilizes a combination of semantic and syntactic features and can identify assertions with 91% accuracy. For verification, we identified salient characteristics of fake tweets by examining three aspects of diffusion: linguistics, the users involved, and the temporal propagation dynamics. We then identified key differences in each of the three characteristics in the spread of true and false fake tweets. A time series of these features extracted for a fake tweet can be classified as predictive of the veracity of that fake tweet using

Hidden Markov Models. The verification algorithm was trained and evaluated on 209 fake tweets collected from real-world events: the 2013 Boston Marathon bombings, the 2014 Ferguson unrest and the 2014 Ebola pandemic, plus many other fake tweets reported on Snopes.com and FactCheck.org (websites documenting fake tweets). The system can predict the veracity of fake tweets with an accuracy of 75% before verification by trusted channels (trustworthy major governmental or news organizations). The ability to track fake tweets and predict their outcomes can have immediate real-world relevance for news consumers, financial markets, journalists, and emergency services, and help minimize the impact of false information on Twitter.

Automatic detection and verification of fake tweets in Twitter are very difficult tasks. Analogous in many ways to speech recognition, they both require extracting weak signals from very noisy environments. Additionally, it is near impossible to get perfect accuracy in both domains. So in addition to accuracy, an insightful way of measuring the performance of our system is to measure the bandwidth reduction of information afforded by our system. This is a theme that we will come back to throughout this thesis. Bandwidth reduction is an important measurement because it can help demonstrate the usefulness and utility of our system in real-world situations. For example, a journalist trying to sort out false and true information from millions of tweets about a real-world event (as was the case with the Boston Marathon bombings), has a Sisyphean task. However, as will be shown in great detail later in this thesis, our system can make the task much less daunting and more manageable for our hypothetical journalist by greatly reducing the amount of information he or she has to sort through.

1.3 Proposed methods :

Due to the complexity of fake news detection in social media, it is evident that a feasible method must contain several aspects to accurately tackle the issue. This is why the proposed method is a combination of Naïve Bayes classifier, Support Vector Machines, and semantic analysis. The proposed method is entirely composed of Artificial Intelligence approaches, which is critical to accurately classify between the real and the fake, instead of using algorithms that are unable to mimic cognitive functions. The three-part method is a combination between Machine Learning algorithms that subdivide into supervised learning techniques, and natural language processing methods. Although each of these approaches can be solely used to classify and detect fake news, in order to increase the accuracy and be applicable to the social media domain, they have been combined into an integrated algorithm as a method for fake news detection.

Furthermore, SVM and Naïve Bayes classifier tend to "rival" each other due to the fact they are both supervised learning algorithms that are efficient at classifying data. Both techniques are moderately accurate at categorizing fake news in experiments, which is why this proposed method focuses on combining SVM and Naïve Bayes classifier to get even more accurate results. In "Combining Naive Bayesian and Support Vector Machine for Intrusion Detection System," the authors integrate both methods of SVM and Naïve Bayes classifier in order to create a more precise method that classifies better than each method individually. They found that their "hybrid algorithm" effectively minimized "false positives as well as maximize balance detection rates," and performed slightly better than SVM and Naïve Bayes classifier did individually (Sagale, & Kale, 2014). Even though this experiment was applied to Intrusion Detection Systems (IDS), it clearly demonstrates that merging the two methods would be relevant to fake news detection.

Moreover, introducing semantic analysis to SVM and Naïve Bayes classifier can improve the algorithm even more. The biggest drawback of Naïve Bayes classifier is that it deems all features of a document, or whichever textual format being used, to be independent even though most of the time that is not the situation. This is a problem due to lowered accuracy and the fact that relationships are not being learned if everything is assumed to be unrelated. As we mentioned earlier, one of the biggest advantages of semantic analysis is that this method is able to find relationships among words. Thus, adding semantic analysis helps fix one of the biggest weaknesses of Naïve Bayes classifier.

In addition, adding semantic analysis to SVM can improve the performance of the classifier. In “Support Vector Machines for Text Categorization Based on Latent Semantic Indexing,” the author shows that combining the two methods improves the efficiency due to “focusing attention of Support Vector Machines onto informative subspaces of the feature spaces,” (Huang, 2001). In the experiment, semantic analysis was able to capture the “underlying content of document in semantic sense,” (Huang, 2001). This improved the efficiency of SVM since the method would waste less of its time classifying meaningless data and spend more time organizing relevant data with the help of semantic analysis. As outlined earlier, a huge benefit of semantic analysis is its ability to extract important data through relationships between words; hence, semantic analysis is able to use its fundamental benefit to further improve SVM.

2.PROJECT PLAN

2.1 Roles and Responsibility:

Roles and responsibility of every member in group in given below:

ROLES	RESPONSIBILITIES
Piyusha Dhavale	Requirement gathering, Diagrams , Backend Development
Vaishnavi Gabda	Requirement gathering, Diagrams , Backend Development
KartikiGangthade	Requirement gathering, Diagrams , Frontend Development
Shivani Kulkarni	Requirement gathering, Diagrams , Frontend Development

Table 2.1: Roles and Responsibility

2.2 Software Model:

- For this project, we use iterative model.
- Iterative process starts with a simple implementation of a subset of the software requirements and iteratively enhances the evolving versions until the full system is implemented.
- At each iteration design modifications are made and new functional capabilities are added. The basic idea behind this method is to develop a system through is to develop a system through repeated cycles and in smaller portions at a time.

2.3 Schedule of Project:

Month Scheduled	Phase	Number of Days Required	Work Done
December	Topic Searching	7 days	Topic Searched
December	Topic Selection	4 days	Topic Selected
December – January	Project Confirmation	1 day	Project Confirmed
January	Requirement Analysis	7 days	Requirement Analysis Done
January	Requirement Gathering	7 days	Requirement Gathering Done
January – February	Designing	14 days	Designing Done
February	Designing Test	5 days	Testing Done
March	Database Creation	10 days	Database Created
March	Coding	30 days	Coded different modules
April	Database and Modules Connectivity	15 days	Connectivity Done
April	Testing of Project	10 days	Project Tested
April	Result Analysis	5 days	Analysis Done

Table 2.3: Schedule of Project

3. REQUIRMENT ANALYSIS

3.1 Hardware Requirements:

Processor	-	Core2Duo
Speed	-	2.1 GHz
RAM	-	2 GB(min)
Hard Disk	-	60 GB
Key Board	-	Standard Windows Keyboard
Mouse	-	Two or Three Button Mouse
Monitor	-	SVGA

3.2 Software Requirements:

Operating System	-	Windows 7,8
Programming Language	-	JAVA, JSP
API	-	Twitt4j, StanfordCore/Open Apache NLP
Java Version	-	JDK 1.8 & above
Database	-	MySQL 5.1.73
Tools	-	Netbeans 8.0.1

4. PROJECT DESIGN

4.1 SYSTEM ARCHITECTURE

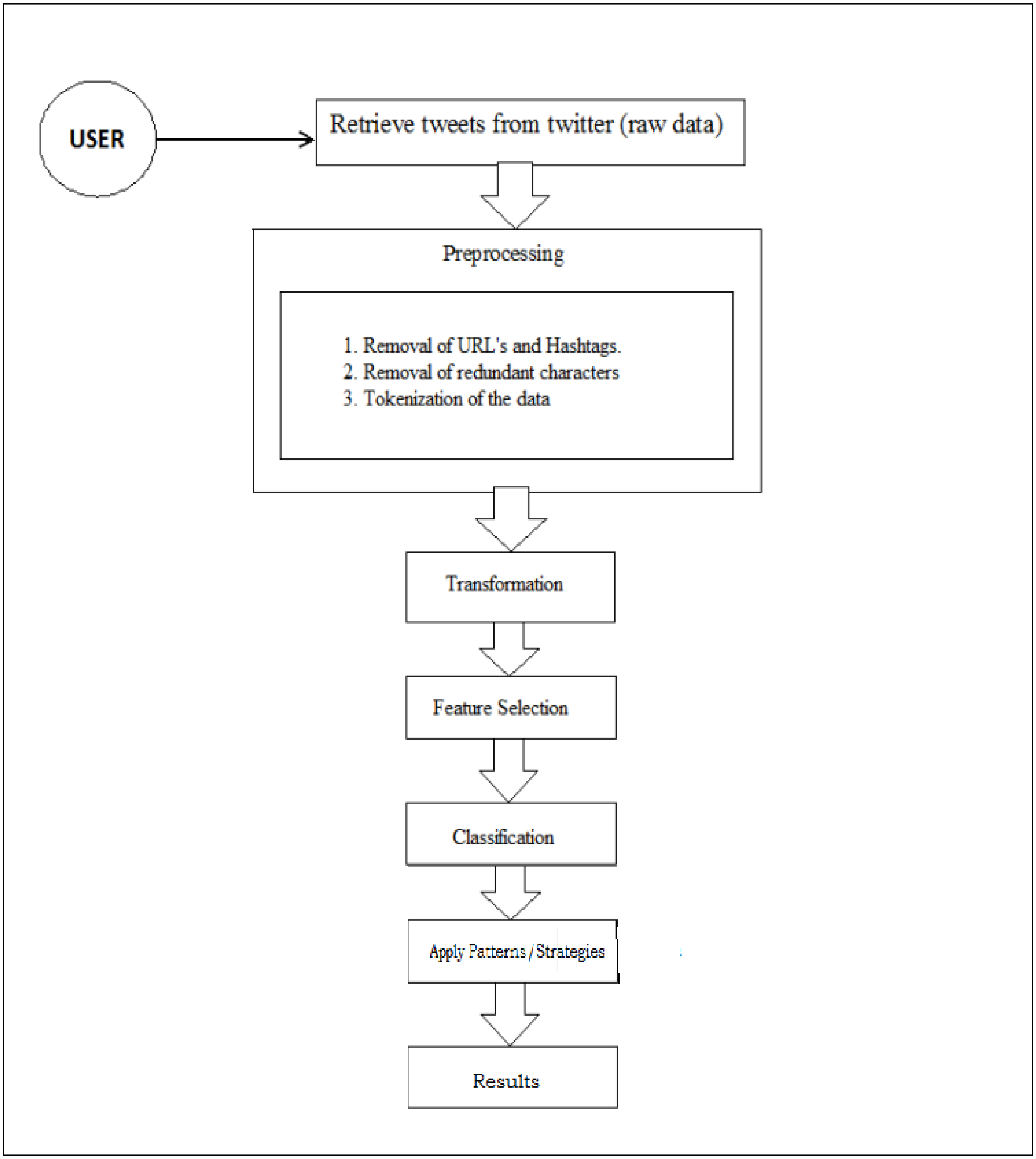


Fig 4.1 System Architecture

Figure shows the general pipeline of our system. As can be seen, the system has two major parts, Hearsift (fake tweet detection) and Fake tweet Gauge (fake tweet verification). The input to Hearsift is the raw tweets about an event of interest, with the output being clusters of tweets with each cluster containing tweets that have propagated through Twitter and that make similar assertions about the event in question (e.g., in the case of the Boston Marathon bombings, the tweets making the assertion that there is a third bomb at Harvard square would all be clustered together). From here on these clusters will be called fake tweets. These fake tweets are the input to the Fake tweet Gauge algorithm, the output of which are a veracity curve for each fake tweet indicating the likelihood that the fake tweet is false or true over time (the algorithm generated a veracity score at every time-step). It should be noted that the system presented hereis modular, meaning that each of the two parts can be replaced by other similar systems. For example, Hearsift can be replaced by other fake tweet detection systems, without effecting the internal workings of Fake tweet Gauge and vice-versa.

RawTweets→Preprocessing→Classification→Pattern Matching→ Predication

4.2 FEATURES

A fake tweet can be described as a temporal communication network, where each node corresponds a communicating user, the edges correspond to communication between nodes and the temporal aspect captures the propagation of messages through the network. The intuition is that there is measurable differences between the temporal communication network corresponding to false and true fake tweets. In order to capture these difference, we need to identify characteristics of fake tweets. It makes sense that these characteristics would be related to either the nodes (i.e. users) in the network, the edges (i.e. messages) in the network or the temporal behaviour of the network (i.e. propagation).

4.2.1 Linguistic

The linguistic features capture the characteristics of the text of the tweets in a fake tweet. A total of 4 linguistic features were found to significantly contribute to the outcome of our models. In the descending order of contribution these features are: ratio of tweet containing negations, average formality & sophistication of the tweets, ratio of tweets containing opinion & insight, and ratio of inferring & tentative tweets. We will now describe each of these features in detail :

- Vulgarity: The presence of vulgar words in the tweet.
- Abbreviations: The presence of abbreviationsin the tweet.
- Emoticons: The presence of emoticons in the tweet.
- Average word complexity: Average length of words in the tweet.
- Sentence complexity: The grammatical complexity of the tweet.

4.2.2 User Identities

The user features capture the characteristics of the users involved in spreading a fake tweet. A total of 6 user features were found to significantly contribute to the outcome of our models. In the descending order of contribution these features are: controversiality, originality, credibility, influence, role, and engagement. We will now describe each of these features in detail.

4.2.3 Propagation Dynamics

The propagation features capture the temporal diffusion dynamics of a fake tweet. A total of 7 propagation features were found to significantly contribute to the outcome of our models. In the descending order of contribution these features are: fraction of low-to-high diffusion, fraction of nodes in largest connected component (LCC), average depth to breadth ratio, ratio of new users, ratio of original tweets, fraction of tweets containing outside links, and the fraction of isolated nodes. All of these features are derived from a fake tweet’s diffusion graph. Before we describe these features in detail, we need to explain how to diffusion graph was created.

4.3 CONSTRAINT

4.3.1 Data Management Constraints :

System shall be able to interface with other components according to their specifications.

4.3.2 Operational Constraints :

The system is limited by its operating server in terms of the maximum number of users it can support at a given time.

4.3.3 Site Adaptation Constraints :

The component will be adapted to the overarching system at the conclusion of the system creation.

4.3.4 Design Standards Compliance :

The system shall be implemented in Java.

4.3.5 Assumptions and dependencies:

Most of the tweets are redundant and twitter API has limits to fetch or search tweets about something. NLP API depends on JDK1.8

4.3.6 System Administrators:

System administrators are primarily responsible for maintaining the users of system and access rates of users for APIs.

4.4 MATHEMATICAL MODEL AND ITS DESCRIPTION

Let S be the closed system defined as,

S = {Ip, Op, A, Ss, Su, Fi}

Where, Ip=Set of Input, Op=Set of Output, Su= Success State, Fi= Failure State and A= Set of actions, Ss= Set of user's states.

- Set of input=Ip={username, password}
- Set of actions =A={F1,F2,F3,F4,F5,F6} Where,
    - F1= Authentication of user
    - F2 =Fetching Tweets from twitter
    - F3 = Compare all Tweets
    - F4 =Influence of negativity spread by tweets
    - F5= Classification on tweets
    - F6= Show Result
- Set of user's states=Ss={registration state, login state, selection of tweets, feature selection, classification, logout}
- Set of output=Op={Show twits analysis results}
- Su=Success state={Registration Success, Login Success, Fetch/Search tweets success}
- Fi=Failure State={Registration failed, Login failed,API failure}
- Set of Exceptions= Ex ={NullPointerException while various states, RecordNotFound (InvalidPassword) state , NullValues Exception while fetching tweets, Limit exaust while fetching tweets}

4.5 Our Contribution

Our contribution in the system is that most of previous work focuses on only sentiment analysis of tweets and its impact on for example product reviews or opinions. We will use sentiment analysis for just classification purpose along with various patterns applying on it which will detect for genuine sources and tweets about various social issues. We will be predicting negative impact spread through it and will warn users about such people and tweets.

4.6 Modification in existing technique.

Existing sentiment analysis techniques are mostly by using only APIs, we additionally will apply TF-IDF algorithm to tweets to cross check API result and algorithm result which in case will increase the accuracy of results.

4.7 Novel Technique

Pattern applied on tweets and classification with sentiment analysis using API and algorithm is the novel approach of this project. Modification to API and addition is as explained earlier and patterns to apply on tweets are as in following table.

Patterns	Description
atti_cnt	The number of users who have favored this weibo.
cmt_cnt	The number of users who have commented this weibo.
repo_cnt	The number of users who have reposted this weibo.
sent_score	Sentiment Score of the weibo.
pic_cnt	The number of pictures posted in this weibo.
tag_cnt	The no of #topics in this weibo.
mention_cnt	The number of @mentions in this weibo.
smiley_cnt	The number of smileys in this weibo.
qm_cnt	The number of question mark in this weibo.
fp_cnt	The number of first person pronouns in his weibo.
Length	The length of the weibo.
is_rt	Whether a Weibo is a repost.
Hour	The hour the weibo was posted.
Source	How the weibo was posted.

Table 4.7: Pattern Description

4.8.DIAGRAMS

4.8.1 Use Case

Use case diagrams are a set of use cases, actors, and their relationships. They represent the use case view of a system. A use case represents a particular functionality of a system. Hence, use case diagram is used to describe the relationships among the functionalities and their internal/external controllers. These controllers are known as actors.

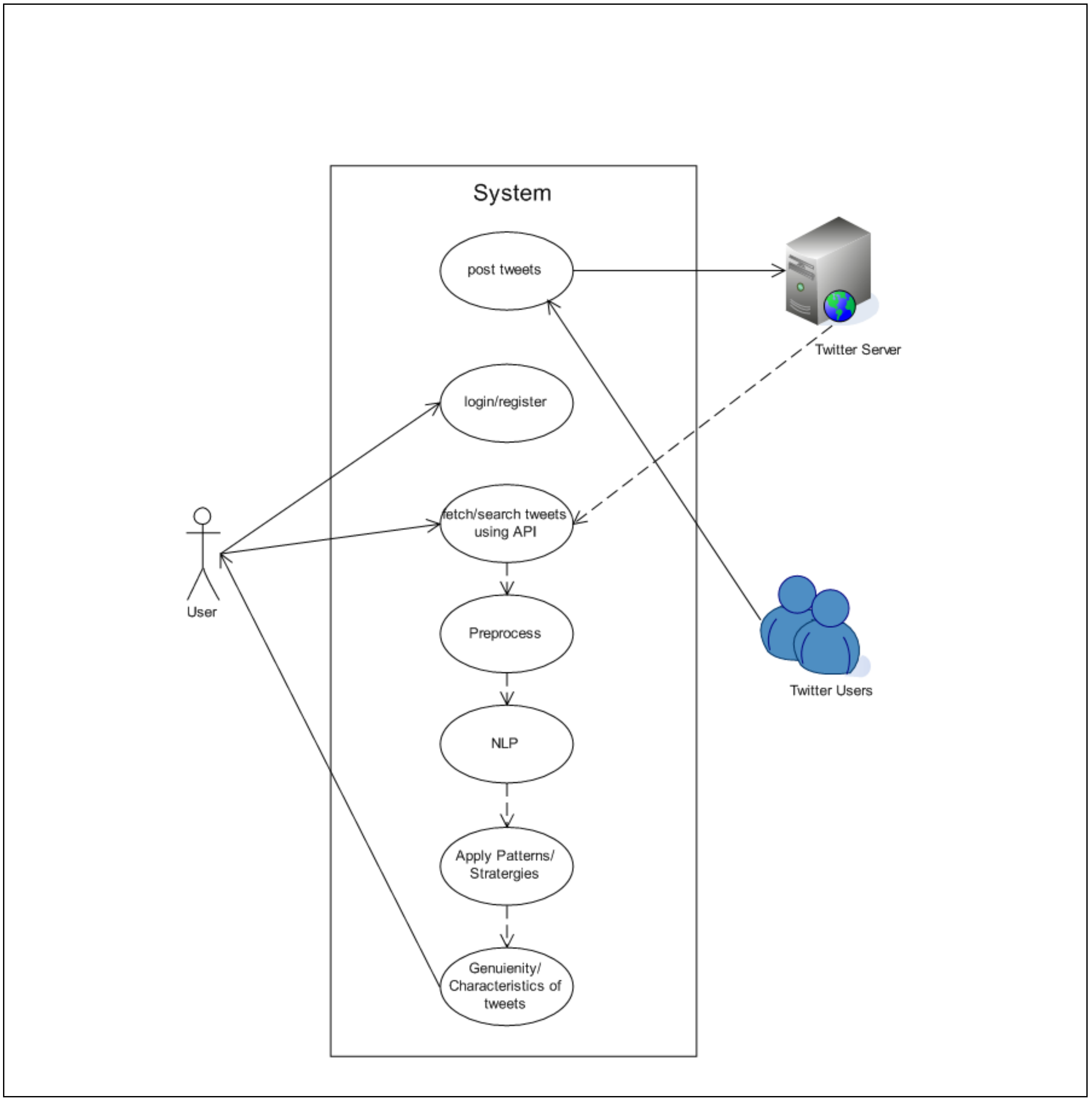


Fig 4.8.1 Use Case

4.8.2 Activity diagram

Activity diagram describes the flow of control in a system. It consists of activities and links. The flow can be sequential, concurrent, or branched. Activities are nothing but the functions of a system. Numbers of activity diagrams are prepared to capture the entire flow in a system. Activity diagrams are used to visualize the flow of controls in a system. This is prepared to have an idea of how the system will work when executed.

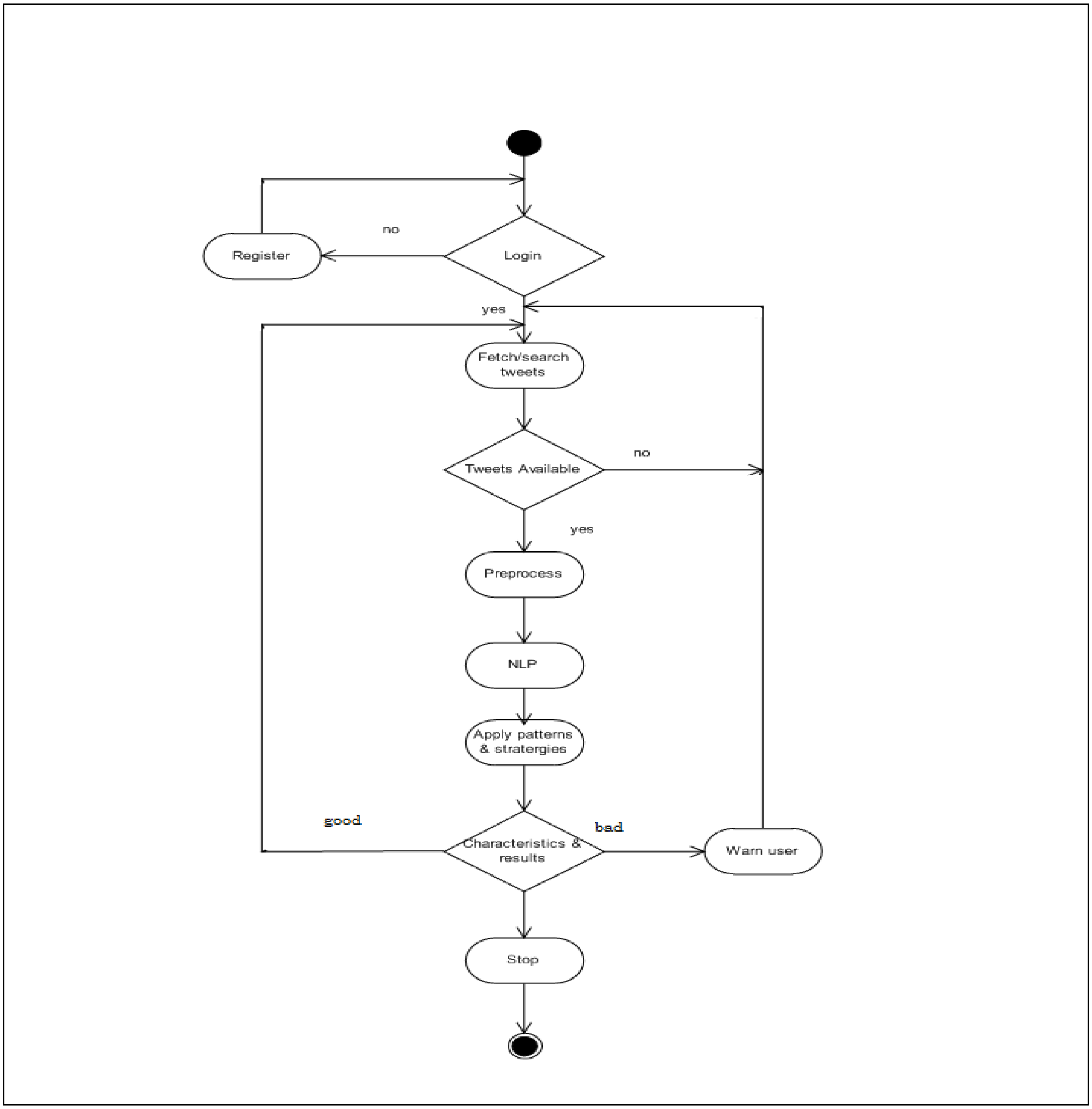


Fig 4.8.2 Activity diagram

4.8.3 Class Diagram

Class diagrams are the most common diagrams used in UML. Class diagram consists of classes, interfaces, associations, and collaboration. Class diagrams basically represent the object-oriented view of a system, which is static in nature. Active class is used in a class diagram to represent the concurrency of the system. Class diagram represents the object orientation of a system. Hence, it is generally used for development purpose. This is the most widely used diagram at the time of system construction.

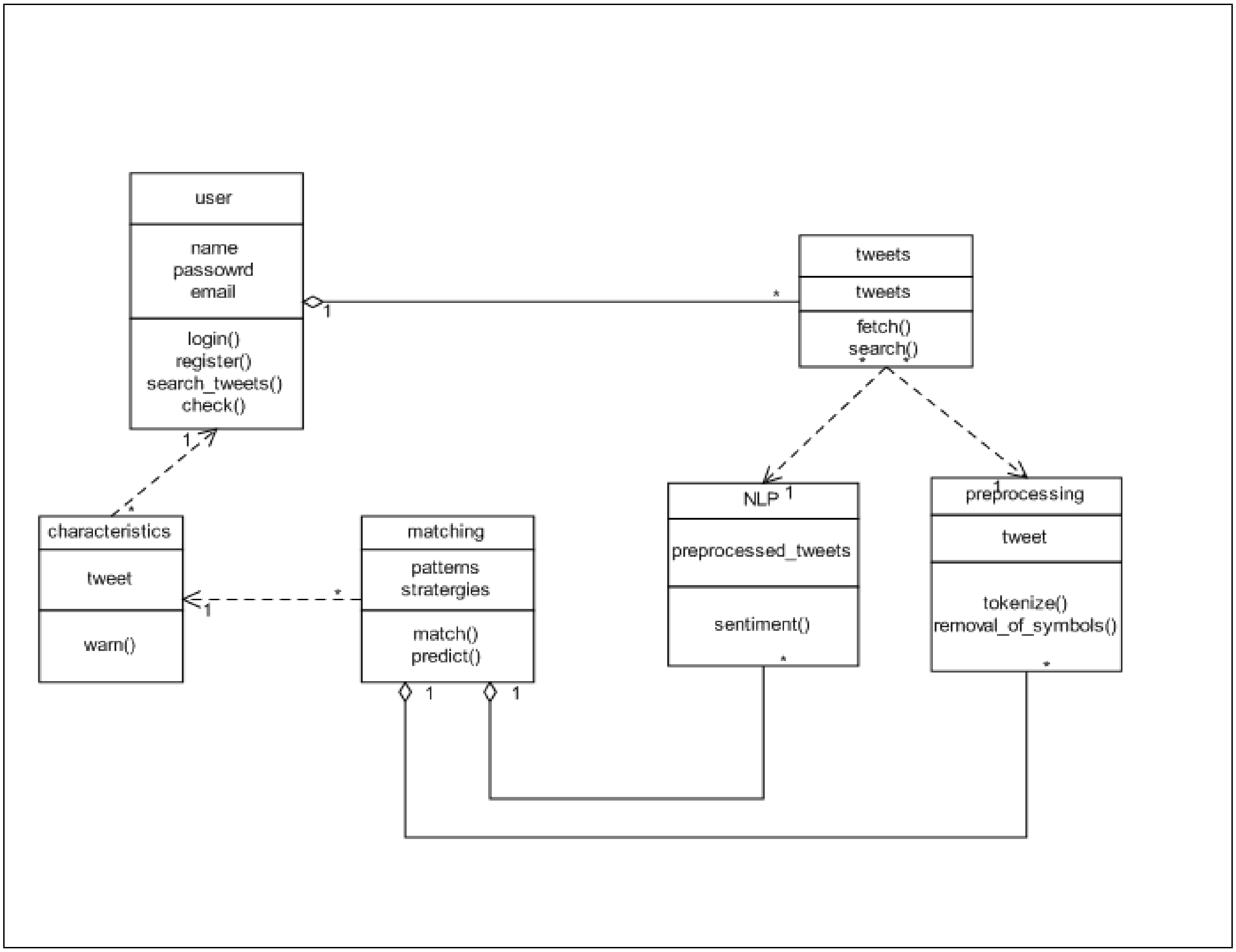


Fig 4.8.3 Class Diagram

4.8.4 Component Diagram

Component diagrams represent a set of components and their relationships. These components consist of classes, interfaces, or collaborations. Component diagrams represent the implementation view of a system. During the design phase, software artifacts (classes, interfaces, etc.) of a system are arranged in different groups depending upon their relationship. Now, these groups are known as components. Finally, it can be said component diagrams are used to visualize the implementation.

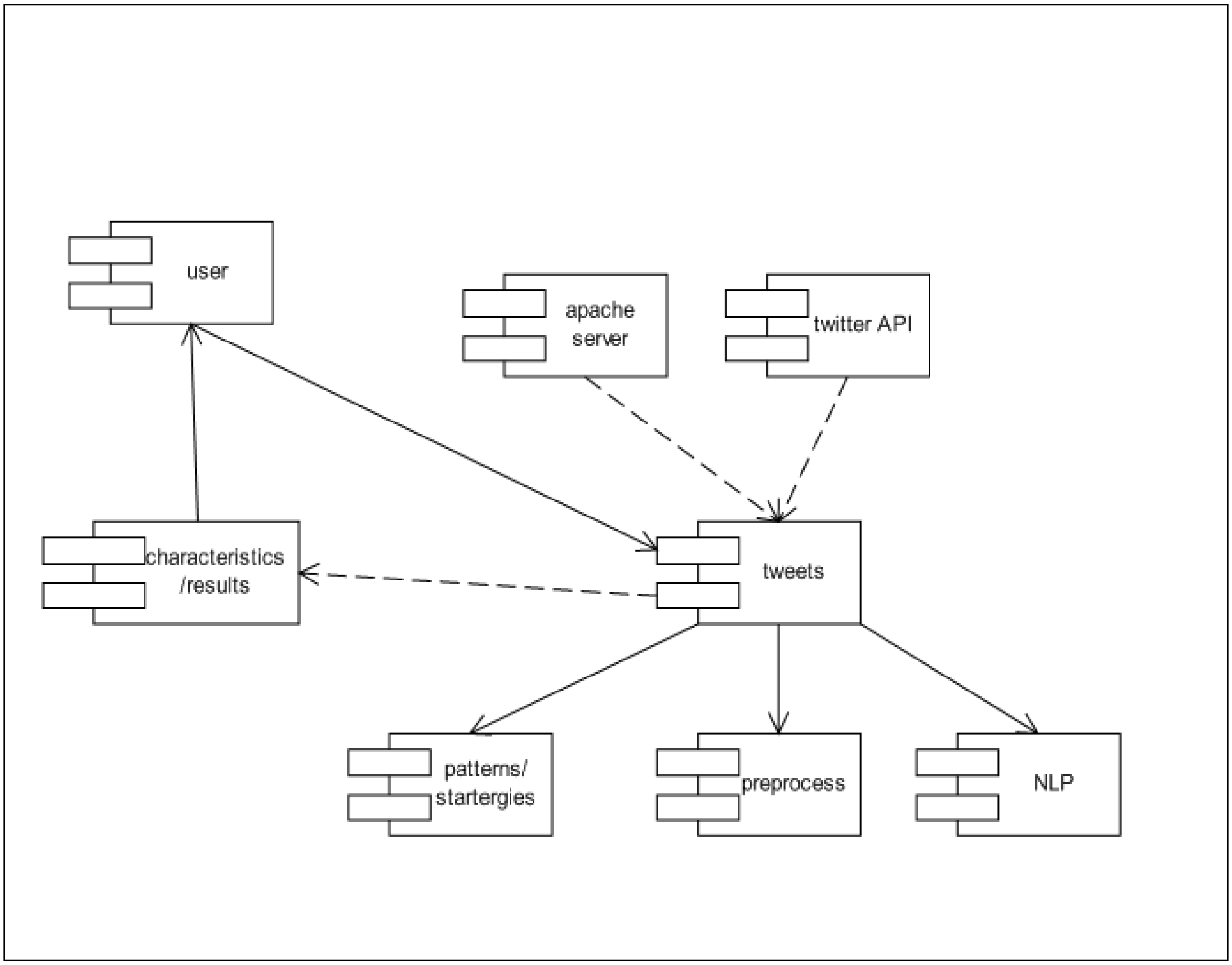


Fig 4.8.4 Component Diagram

4.8.5 Sequence Diagram

Sequence diagrams are a popular dynamic modeling solution in UML because they specifically focus on lifelines, or the processes and objects that live simultaneously, and the messages exchanged between them to perform a function before the lifeline ends.

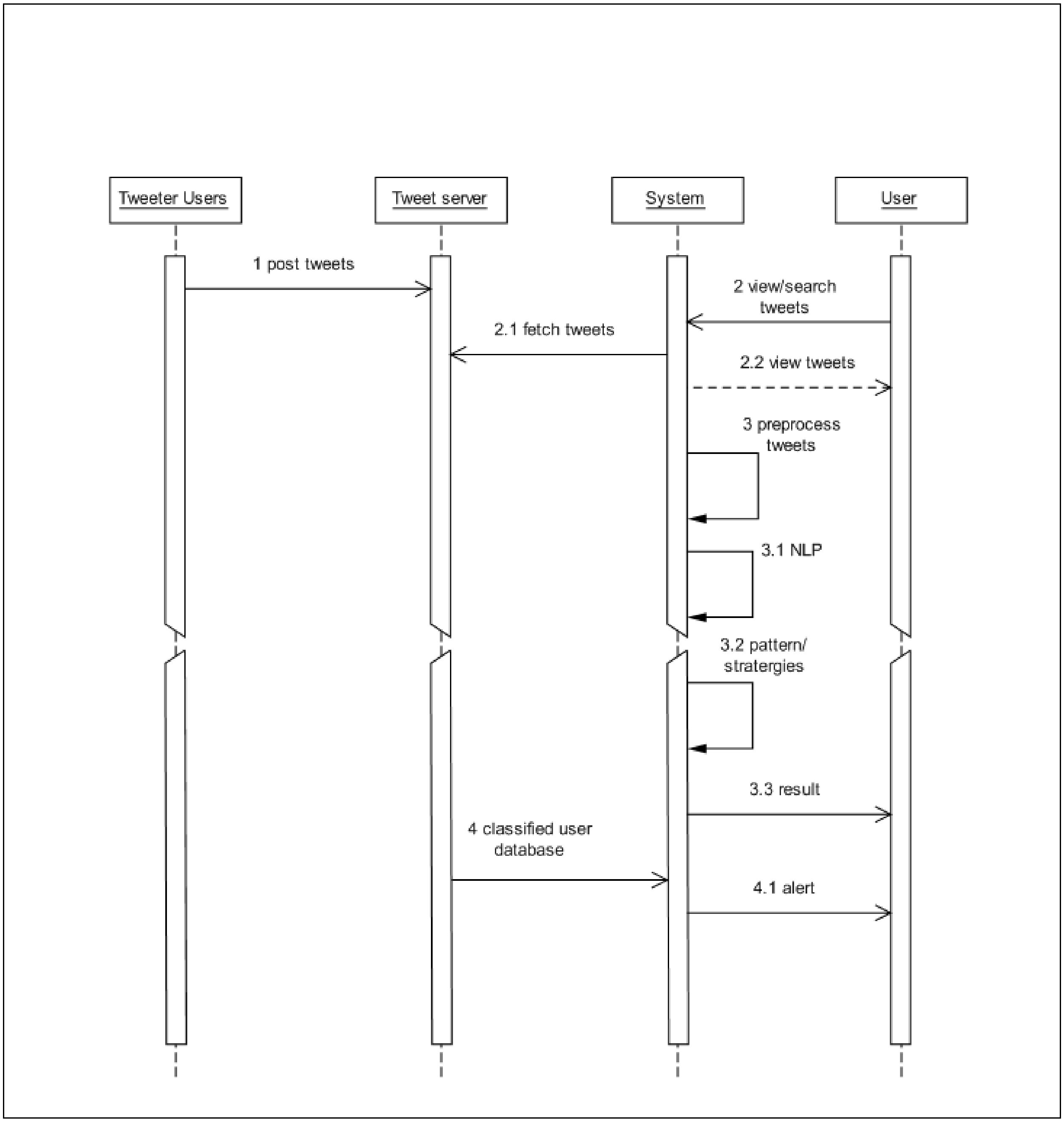


Fig 4.8.5 Sequence Diagram

4.8.6 Deployment Diagram

Deployment diagrams are a set of nodes and their relationships. These nodes are physical entities where the components are deployed. Deployment diagrams are used for visualizing the deployment view of a system. This is generally used by the deployment team.

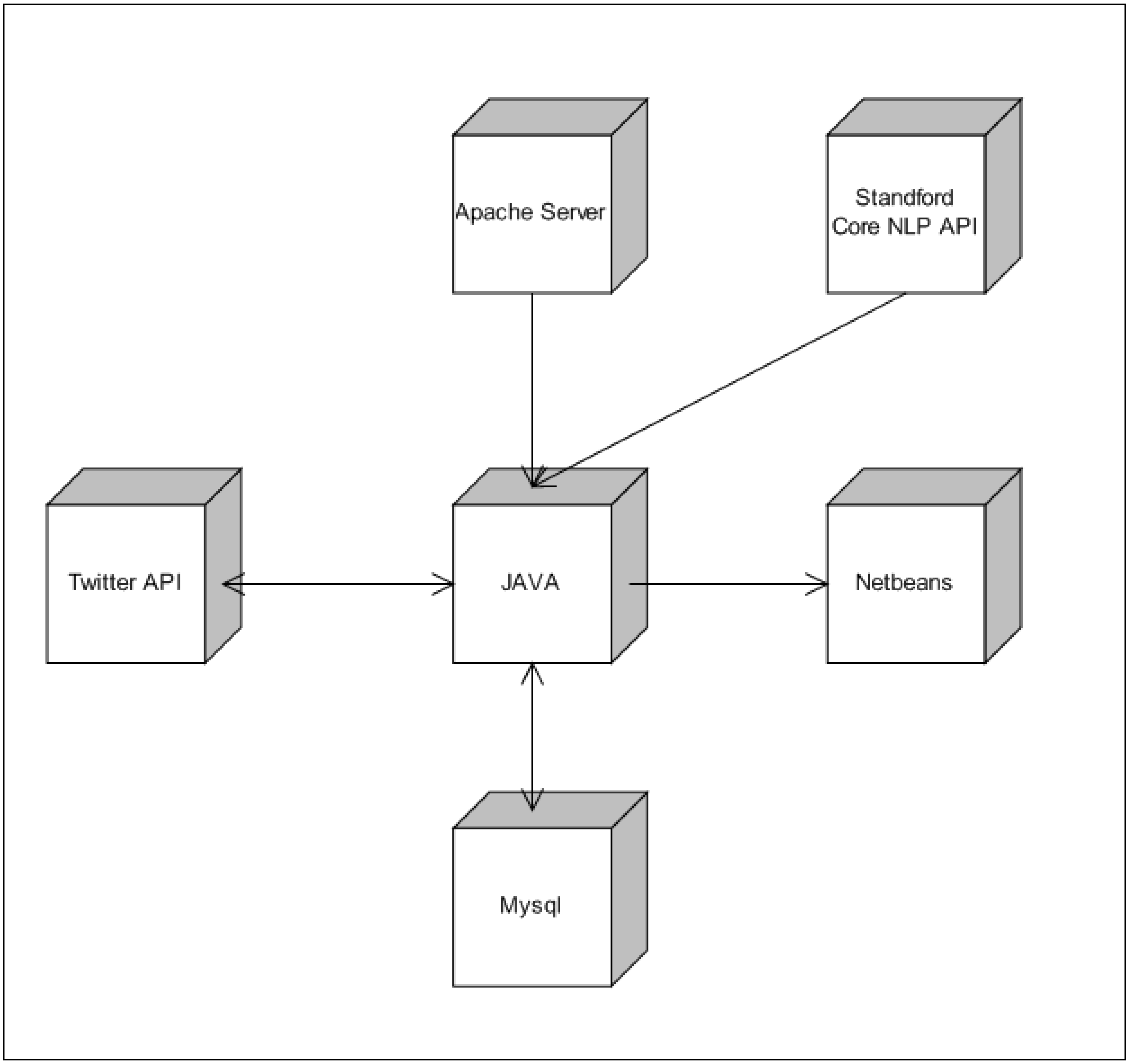


Fig 4.8.6 Deployment Diagram

5.EXPERIMENTAL SETUP

Our experimental setup is as follows.

5.1 Dataset

In the work conducted in this project, we use the twitter developer API to fetch live tweets or to search tweets about particular topic. These tweets will be our dataset

5.2 Pre-Processing and Feature Reduction

Natural language processing of the corpus is performed for stop words removal, bag of words extraction and equivalence classes' replacement such that:

- All Twitter usernames, which start with @ symbol, are replaced with the term "USERNAME".
- All URL links in the corpus are replaced with the term "URL"
- Reduce the number of letters that are repeated more than twice in all words.
- For example the word "haaaappy" becomes "haappy" after reduction
- Remove all Twitter hashtags which start with the#.
- Remove all emoticons as they add noise during the training of the classifiers

We choose unigrams (i.e. distinct words in the corpus), as well as, bigrams (i.e. combination of every two consecutive words in the text) as features spaces. For example for a tweet "I Love Kindle, It's Amazing", Unigrams would be {I, Love, Kindle, Its, Amazing}, whereas bigrams would be {I Love, Love Kindle, Kindle Its, Its Amazing}. Consequently, bigrams normally produces larger feature space.

5.3 Performance and Result Evaluation Steps

After pre-processing is done, four different variations of the input dataset are produced:

- Unigram with Term Frequency.
- Bigrams with term polarity
- Bigrams with term Frequency.
- Then we apply Sentiment analysis for each tweet to detect polarity of sentence
- Apply patterns after classification
- Show results

5.4Comparison with earlier work

Parameters	Existing System	Proposed System
Sentiment Analysis	Yes	Yes
Polarity Detection	Somewhat	Yes
Classification	Somewhat	Yes
Pattern Matching	No	Yes
Fake Tweets	No	Yes
Graphical Analysis	No	Yes
User Alerts	No	Yes

Table 5.4 Comparison

6. TESTING

6.1 Testing Plan:

Sr. No.	Type of Test	Description	Hardware/Software Components
1	Requirement Testing	This testing is required because we need to verify whether our requirements are able to solve the current problem or not	Complete Software including GUI.
2	Unit testing	This testing allows us to test individual modules before integrating them together to form a complete module	Data Pre-processing.
3	Integration	This test is important to check whether the modules are giving the same results after integration as before	All adjacent modules
4	Performance	This test is important to calculate the efficiency of the Hardware/Software also helps us to find any performance issue related to the system	All the Software components individually.
5	Security	We have performed this test to check whether privacy is maintained	Provided for tweets.
6	Compliance	This test is performed in order to check whether we are implementing and meeting the defined standards	GUI Components

Table 6.1 Testing Plan

6.2 TESTING TABLE

S.no	Searches	Positive Tweets	Negative Tweets	Rumors
1	Narendra Modi	7	4	4
2	M.S. Dhoni	12	0	6
3	Virat Kohli	6	6	2
4	Donald Trump	15	1	4
5	India	13	2	1
6	Corona	7	8	4
7	Iran	13	2	1
8	Bill Gates	15	0	1
9	Barak Obama	15	4	1
10	Pune	8	7	2
11	Lockdown	10	5	1
12	Java	9	6	1
13	SSC Exams	15	0	1
14	China	6	8	6
15	UdhavThakrey	13	2	4

Table 6.2 Testing Table

6.3 Test Cases

Test Case Id	Test Case Objective	Prerequisite	Steps	Expected Result	Actual Result	Status
TC_1	Check the User Interface of Registration page.	Registration Module	Open the website and Registration page.	Opens the website and registration page.	Registration page opens.	Pass
TC_2	Check working of all the buttons.	Sign Up and Reset button	Check Sign Up and Reset button on registration page.	All buttons are working properly.	Buttons work properly.	Pass
TC_3	Check all the required fields by entering the data and validating.	Fields	Enter data into fields.	Data accepted.	Data accepted.	Pass
TC_4	Test for invalid First name and Last name like: entering numbers or special characters.	First name and last name fields	Enter data into fields.	Data not accepted.	Data not accepted.	Pass
TC_5	Test for some invalid emails with cases like: without @, (.) and without alphabets before @.	Email field	Enter data into the Email field.	Data not accepted.	Data not accepted.	Pass
TC_6	Test for valid email address.	Email field	Enter data into the Email field.	Data accepted	Data accepted	Pass
TC_7	Test for valid but existing email address.	Email field	Enter data into the Email field.	Data not accepted.	Data not accepted.	Pass

TC_8	Test for the invalid mobile number like: entering characters or number less than 10 digits.	Mobile number field	Enter data into the Mobile Number field.	Data not accepted.	Data not accepted	Pass
TC_9	Test for the valid mobile number.	Mobile number field	Enter data into the Mobile Number field.	Data accepted.	Data accepted.	Pass
TC_10	Test for valid Twitter ID.	Twitter ID field	Enter data into Twitter ID field.	Data accepted.	Data accepted.	Pass
TC_11	Test for the invalid username like: entering the invalid username.	Username field	Enter data into Username field.	Data not accepted.	Data not accepted.	Pass
TC_12	Test for the valid username.	Username field	Enter data into Username field	Data accepted.	Data accepted.	Pass
TC_13	Check the password without entering a Caps lock character , a number or less than 6 characters.	Password field	Enter data into Password field	Data not accepted.	Data not accepted.	Pass
TC_14	Check for the valid password including one Caps lock character, small characters, a number and minimum 6 characters.	Password field	Enter data into Password field	Data accepted.	Data accepted.	Pass

TC_15	Check the Sign Up button.	Sign Up button	Click on Sign Up button.	Redirects to the Home page.	Redirects to the Home page.	Pass
TC_16	Check the Reset button.	Reset button.	Click on Reset button.	Reset all the values on Registration page.	All values are reset on Registration page.	Pass

Table 6.3.1 Registration Module

Test cases	Test Case Objective	Pre-Requisite	Steps	Actual Result	Expected Result	Status
TC_1	Open your website	Website	Open your website in anyBrowser.	Open the website in any Browser	Website open.	Pass
TC_2	Check the UI of User Login screen	User Login Page	Open the User Login Page	Opens the User Login Page	User Login Page Open	Pass
TC_3	Check whether the User Login Tab is going on User Login Page.	User Login Tab	Click on the User Login Tab.	Opens the User Login Page by clicking on the User Login Tab.	User Login Page gets open by clicking the User Login Tab.	Pass
TC_4	Verify if a user will be able to login with a valid username and valid password	Username and Password field	Click on Username and Password field	Username and Password field should be focused	Username and Password field Focused	Pass
TC_5	Verify if a user cannot login with a valid username and an invalid password.	Username and Password field	Click on Username and Password field	Invalid Username and Password	Sign in not successful	Pass
TC_6	Verify the User Login page for both, when the field is blank and Sign in button is clicked.	Username and Password field	Click on Username and Password field	Invalid Credentials	Invalid Credentials	Pass
TC_7	Verify the ‘Reset’ functionality.	Reset field	Click on Reset field	Reset Password Through OTP system.	Password resets successfully	Pass
TC_8	Verify if password field is either visible as	Password Field	Enter Password	Test in bullets Format	Test in bullets Format	Pass

	asterisk or bullet signs.					
TC_9	Verify if a user is able to login with a new password only after he/she has changed the password.	Password Field	Enter Password	User is able to change password	User is able to change password	Pass
TC_10	Verify if the User Login page allows to log in simultaneously in different systems.	Two or more systems with the site.	Open User Login Page.	User is able to login simultaneously in different systems.	User is able to login simultaneously in different systems.	Pass

Table 6.3.2:User Login Module

Test-cases	Test Case Objective	Pre-Requisite	Steps	Actual Result	Expected Result	Status
TC_1	Open your website	Website	Open your website in any Browser.	Open the website in any Browser.	Website opens.	Pass
TC_2	Check the UI of Admin Login Screen	Admin Login Page	Open the Admin Login Page	Opens the Admin Login Page	Admin Login Page Open	Pass
TC_3	Check whether the Admin Login Tab is going on Admin Login Page.	Admin Login Tab	Click on the Admin Login Tab.	Opens the Admin Login Page by clicking on the Admin Login Tab.	Admin Login Page gets open by clicking the Admin Login Tab.	Pass
TC_4	Verify if a admin will be able to login in with a valid Admin Name and valid Password.	Admin Name and Password field	Click on Admin Name and Password field	Admin Name and Password field should be focused	Admin Name and Password field focused	Pass
TC_5	Verify if a admin cannot login with a valid admin-name and an invalid password.	Admin Name and Password field	Click on Admin Name and Password field	Invalid Admin Name and Password	Sign in not successful	Pass
TC_6	Verify the Admin Login page for both, when the field is blank and Sign in button is clicked.	Admin Name and Password field	Click on Admin Name and Password field	Invalid Credentials	Invalid Credentials	Pass

TC_7	Verify the 'Reset' functionality.	Reset Field.	Click on Reset Field	Reset Password Through OTP system.	Password resets successfully	Pass
TC_8	Verify if the data in password field is either visible as asterisk or bullet signs.	Password Field	Enter Password	Test in bullets format	Test in bullets format	Pass
TC_9	Verify if a admin is able to login with a new password only after he/she has changed the password.	Password Field	Enter Password	Admin is able to change password	Admin is able to change password	Pass
TC_10	Verify if the Admin Login page allows to log in simultaneously in different systems.	Two or more systems with the site.	Open Admin Login Page.	Admin is able to Login simultaneously indifferent systems.	Admin is able to login simultaneously in different systems.	Pass

Table 6.3.3:Admin Login Module

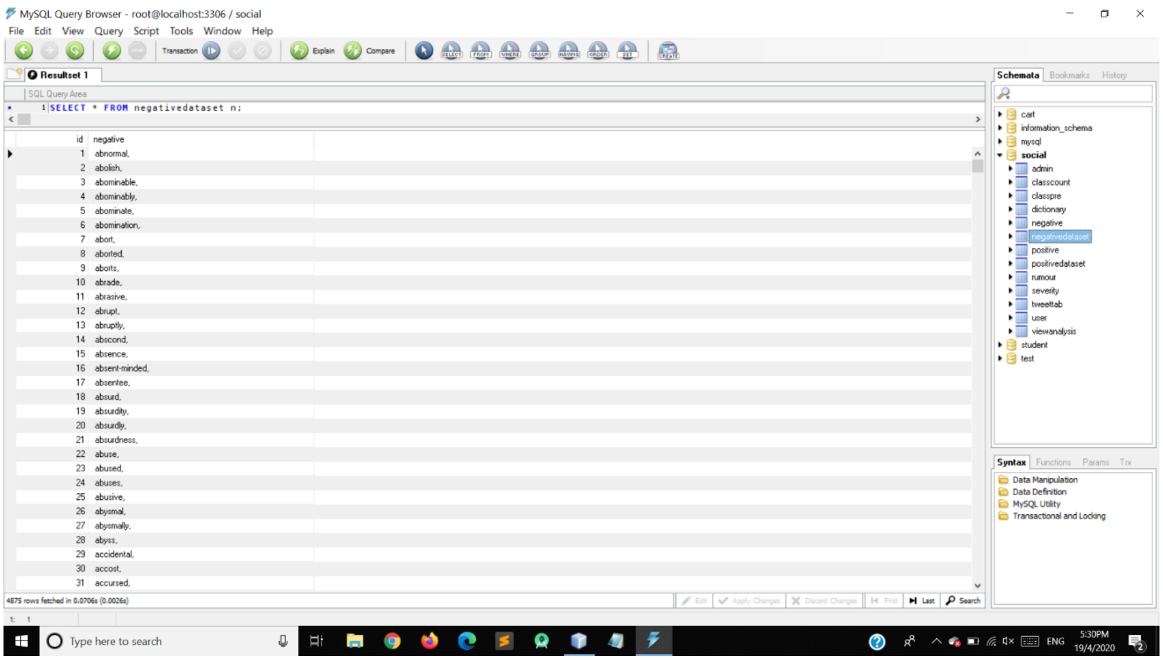
Test Case Id	Test Case Objective	Pre-Requisite	Steps	Expected Result	Actual Result	Status
TC_1	Validity of Search Tweet tab	Search Tweet tab should available	Click the Search Tweet tab	The form displaying the option for searching tweet should display.	The form is displayed	Pass
TC_2	Validity of Textbox for Searching Tweet	Textbox for Searching tweet should available	Type something in textbox	Textbox should active	Textbox is active	Pass
TC_3	Checking for Submit button and Reset button	Submit and Reset button should available	-------------------	Submit and Reset button should available	Submit and Reset button is available	Pass
TC_4	Validity of Submit button	Submit button should available	Click on Submit button	The page containing the result of searched tweet should display	The page containing the result of searched tweet is displayed	Pass
TC_5	Validity of Reset button	Reset button should available	Click on Reset button	Textbox field should reset to blank	Textbox field is reset to blank	Pass
TC_6	Validity of page which is displayed after clicking the submit button	Submit button should available	Click on submit button	The page should contain tweets related to searched query.	Tweets are fetched and a link is provided for observing prediction.	Pass

TC_7	Validity of link which is provided in page of retrieved tweets	Link should available	Click on link	Should navigate to the page which display various graphs and severity of rumors	Navigate to the page which display various graphs and severity of rumors	Pass
TC_8	Validity of Prediction page	Link should Available	Click on link	Should contain correct graphs	Contain correct graphs	Pass

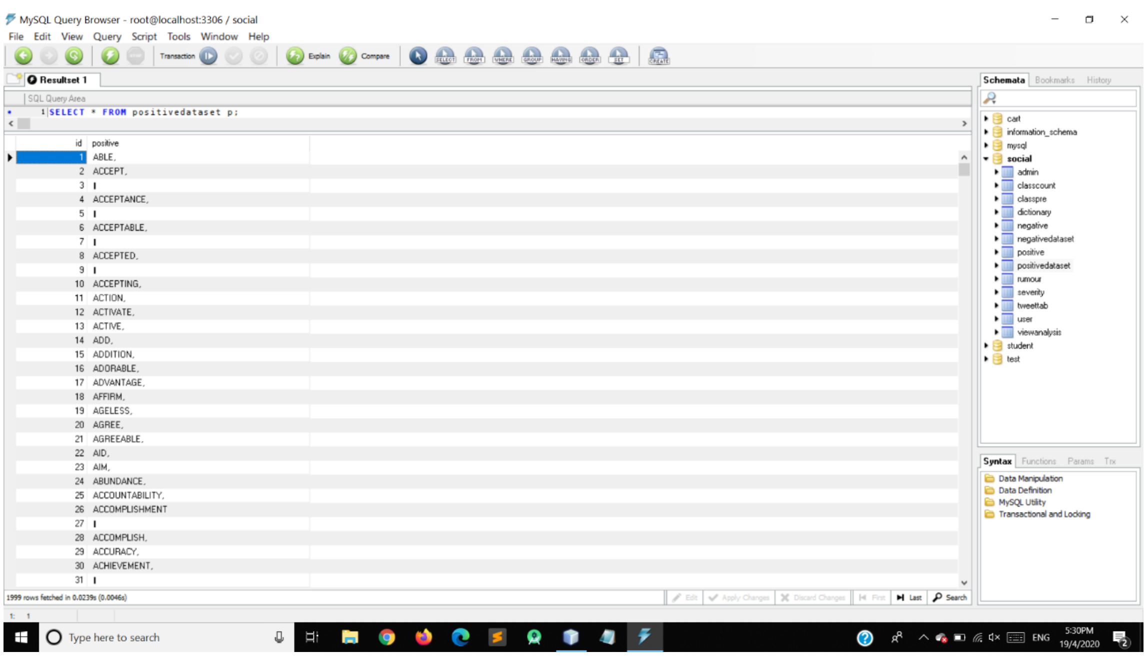
Table 6.3.4: Search Tweet Module

7. SCREEN SHOTS

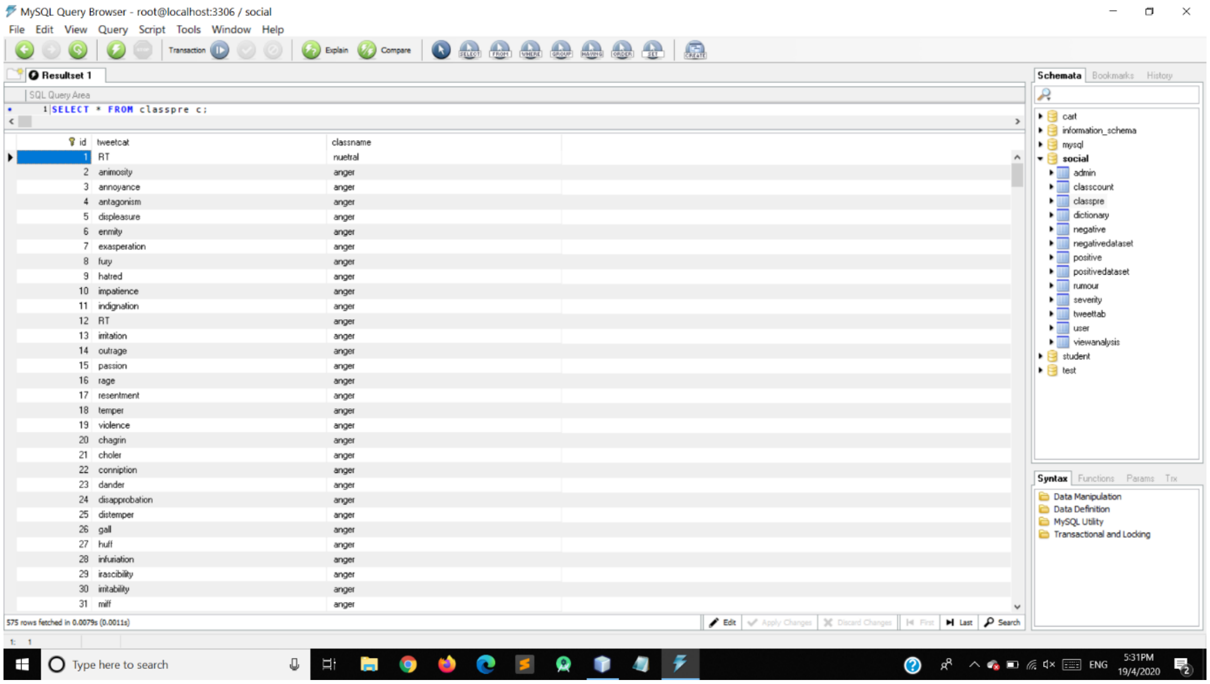
- **Backend : MySQL Query Browser**
  A "social" database is created in which all the tables are present.



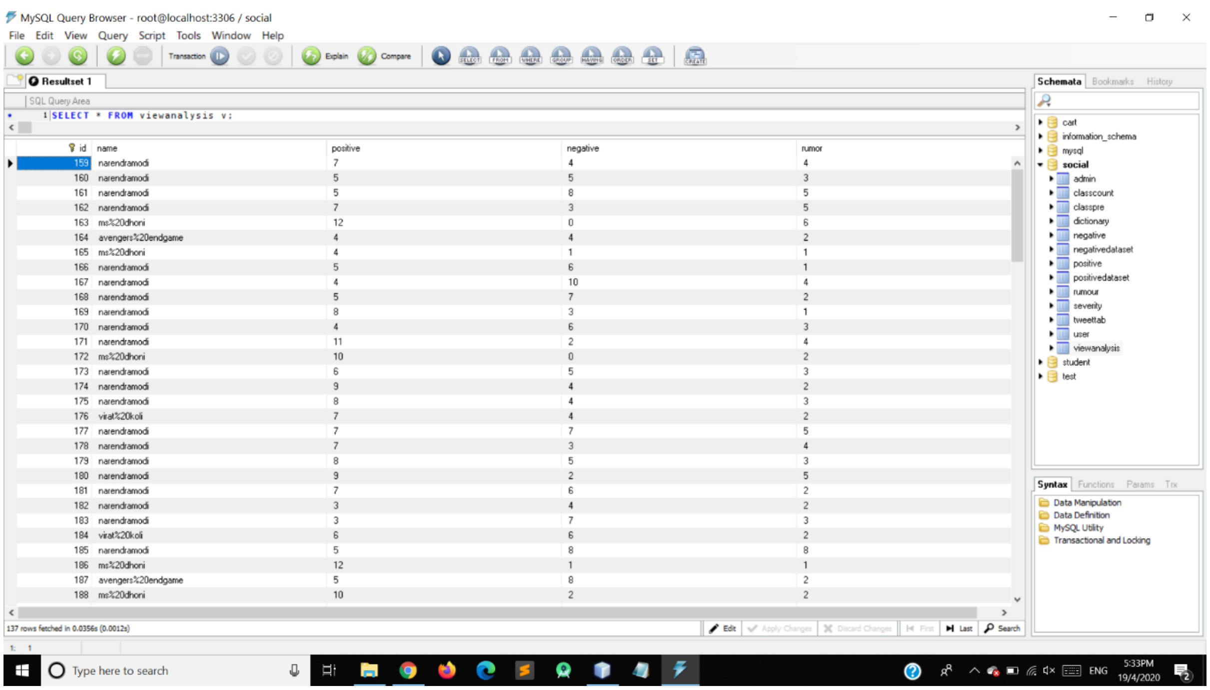
This is the table where all the negative words (a dataset) is stored.



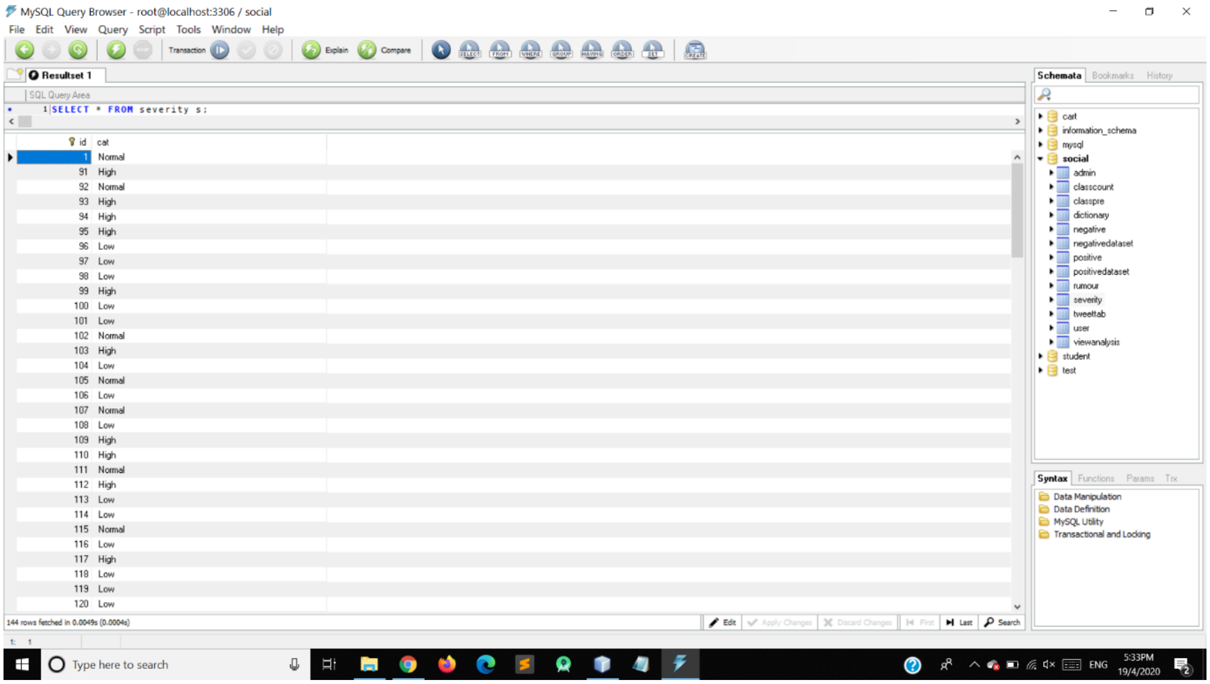
This is the table where all the positive words (a dataset) is stored.



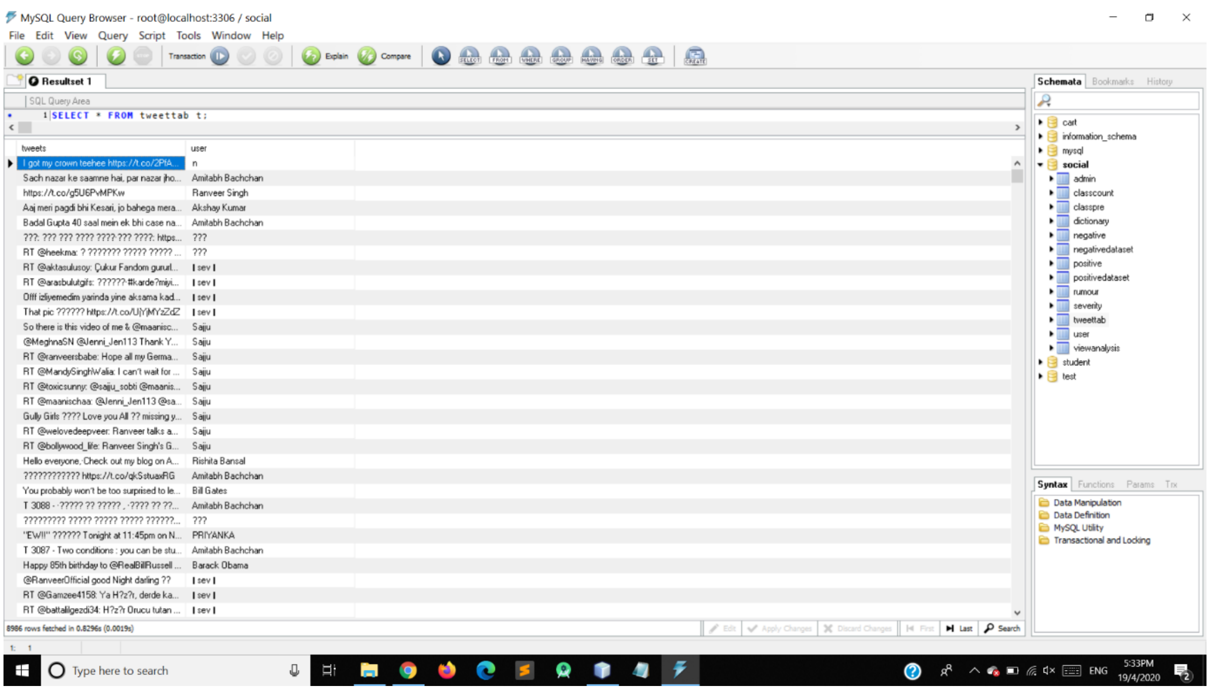
Here , fetched tweets words are stored as behaviour.



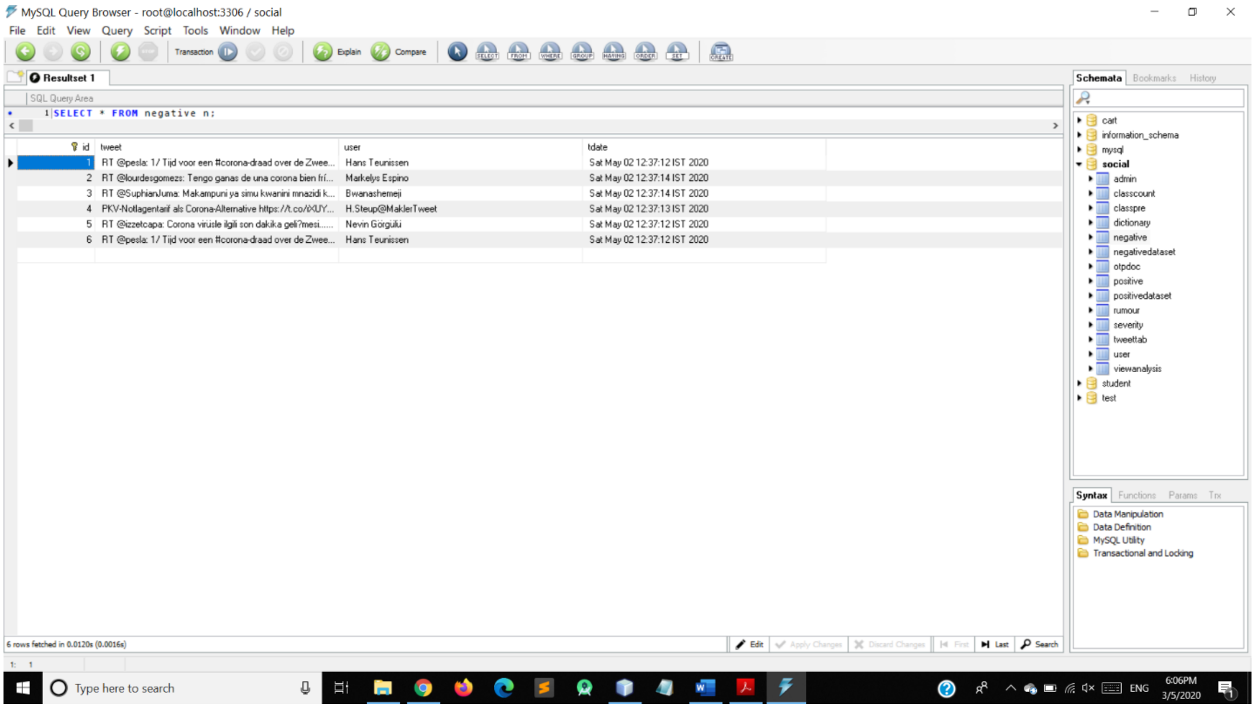
Here, Analysis of the previously searched tweets are stored here.



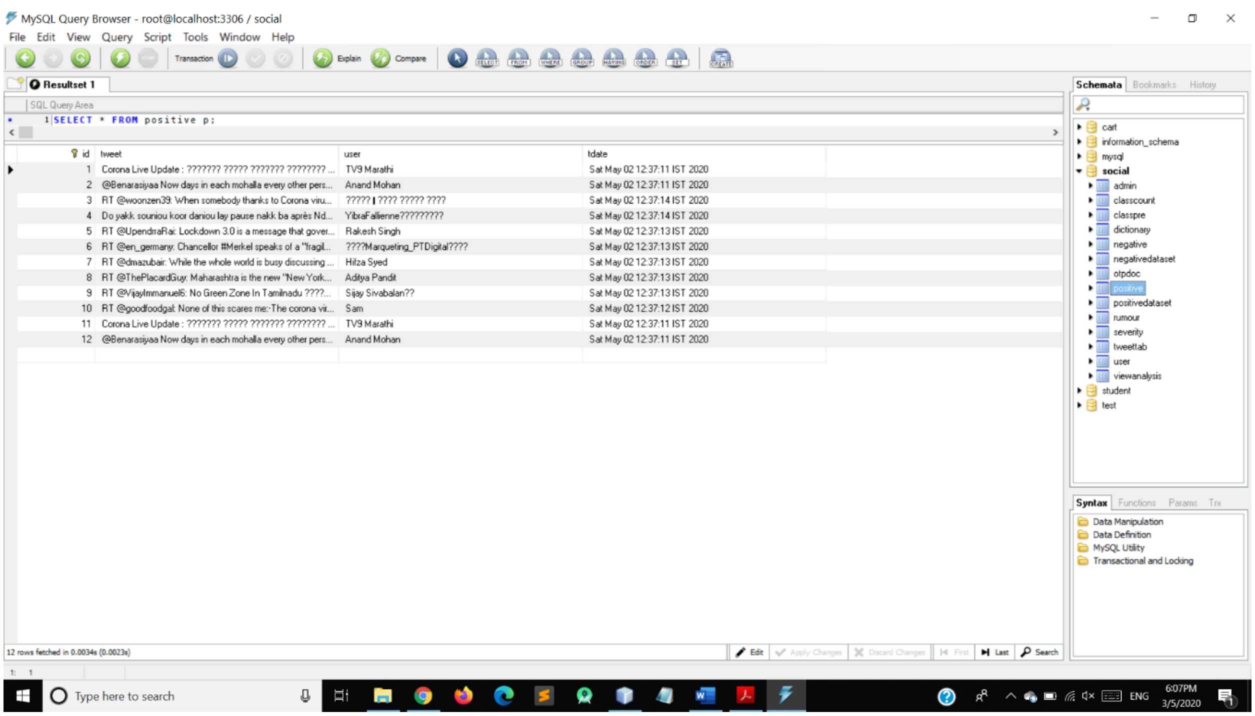
Here, Severity of the previously searched tweets are stored.



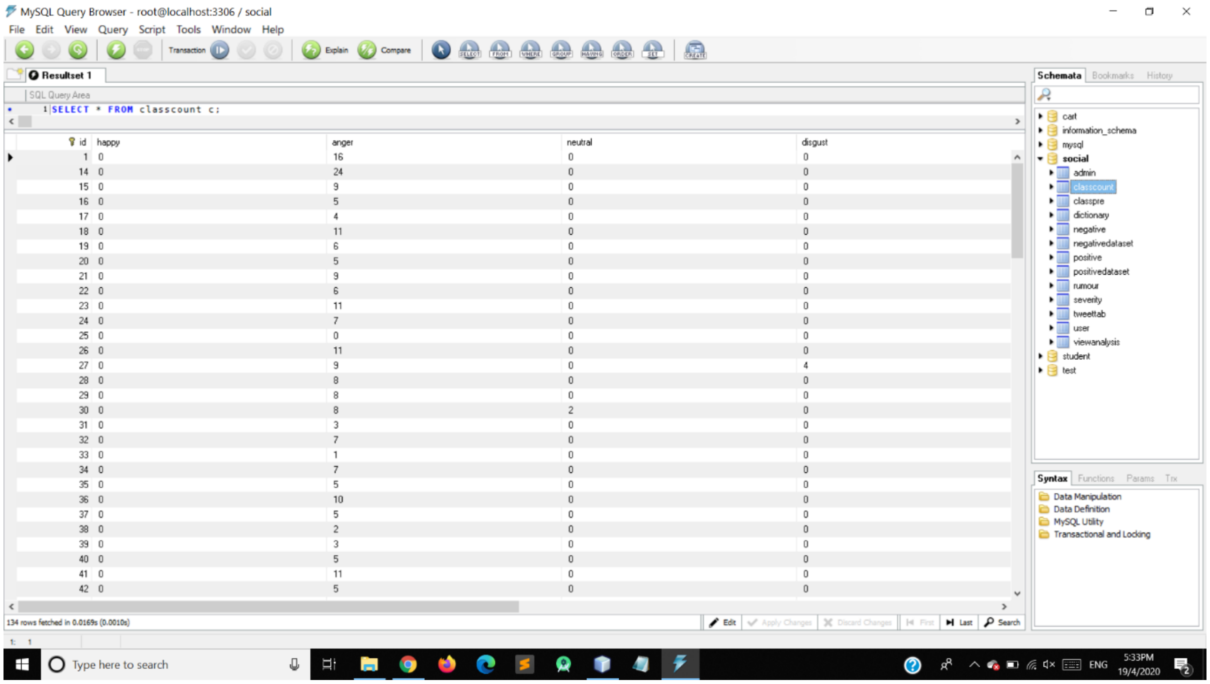
Here, all the tweets searched till date are stored.



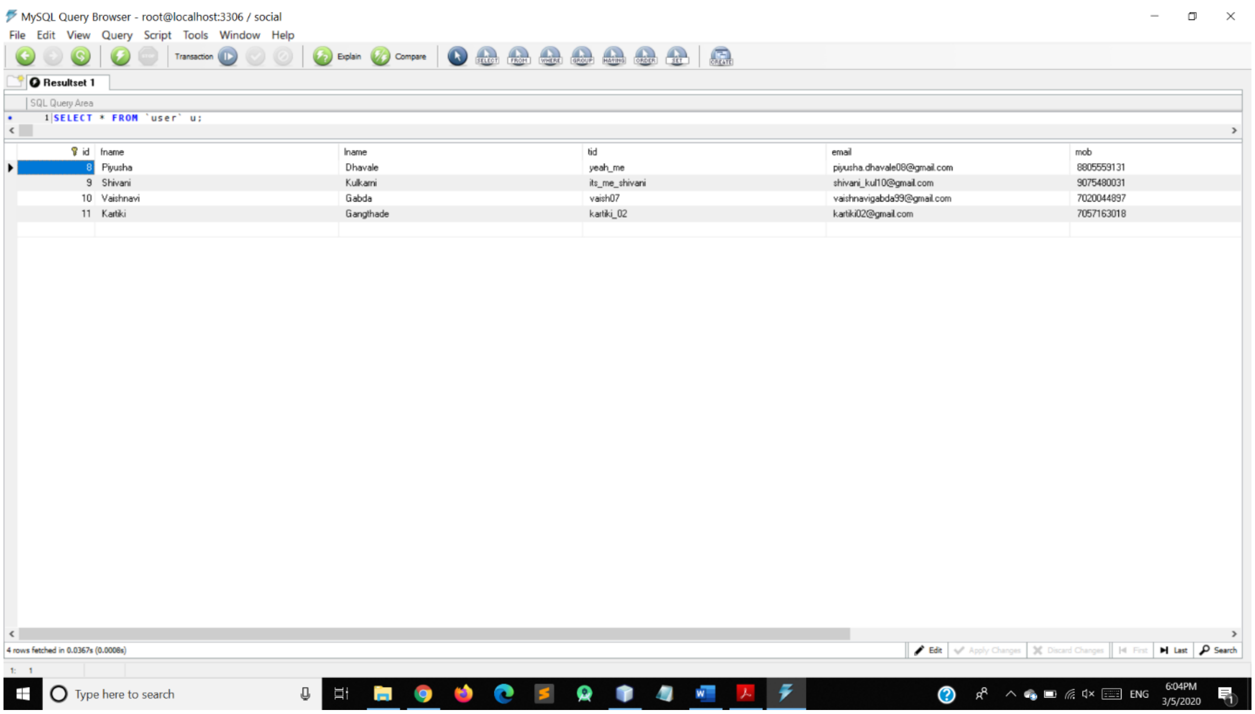
Here, Negative tweets are stored.



Here, Positive tweets are stored.

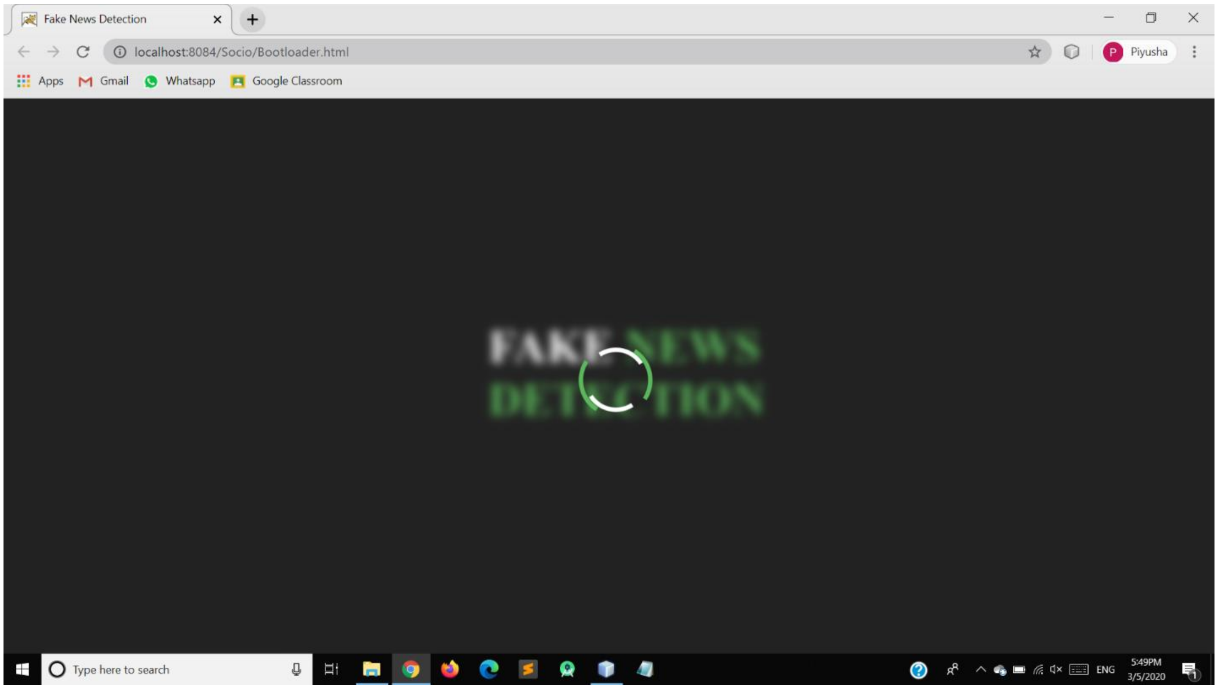


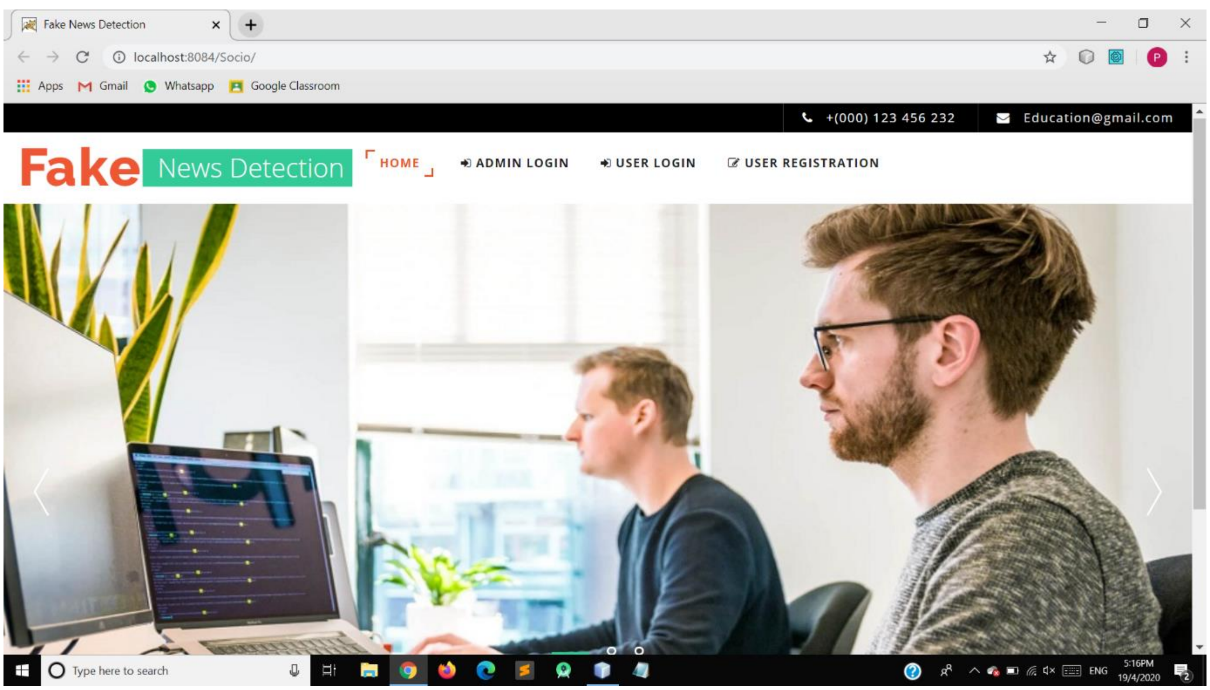
Here, count of sentiments are stored.



Here , the users registered are stored.

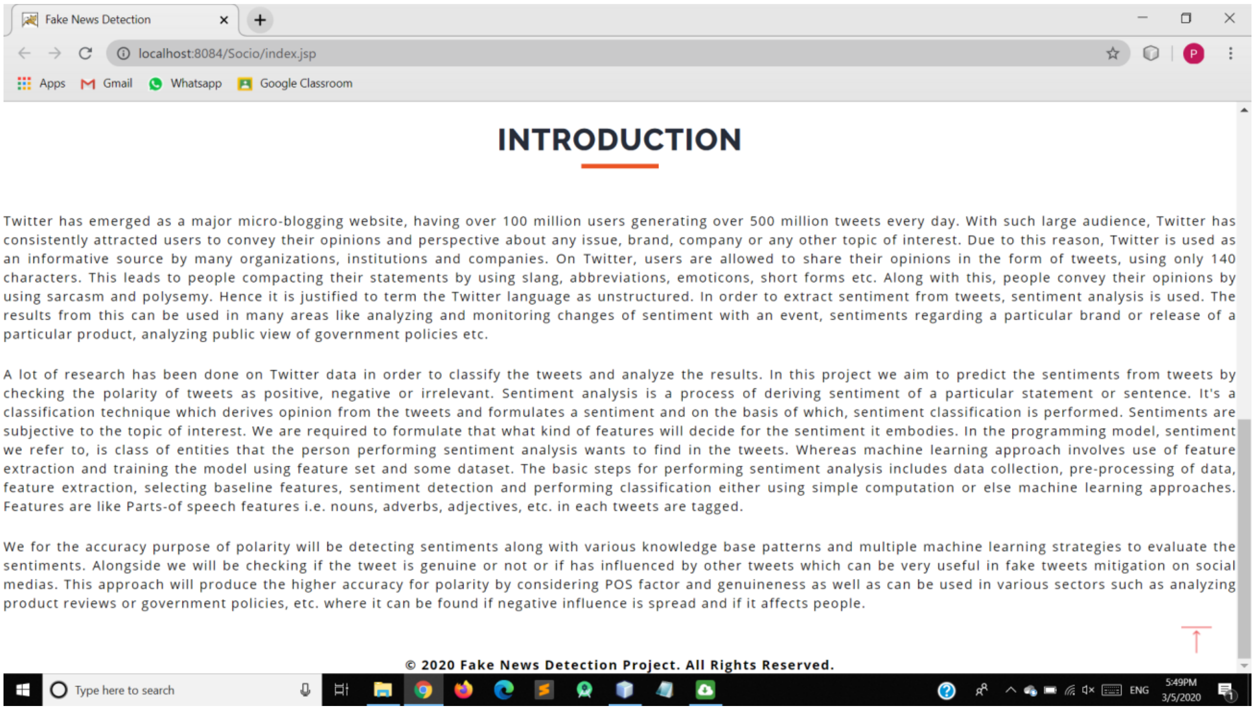
Frontend



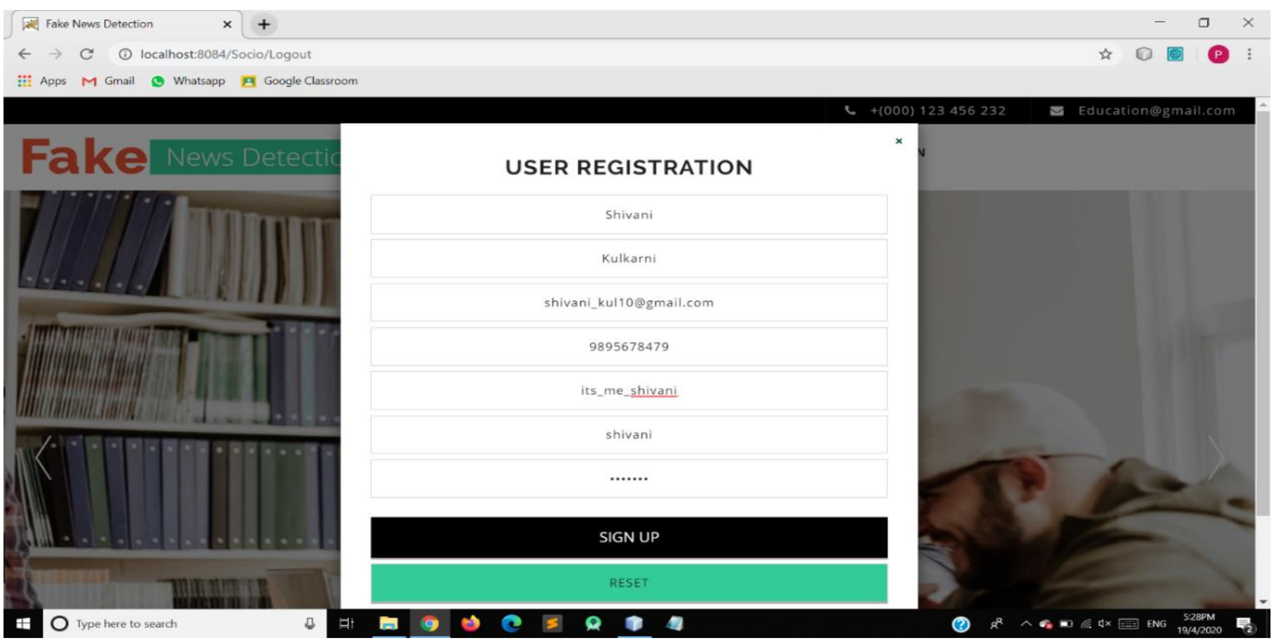


This is the main webpage of the “Fake News Detection” website. It has four tabs as follows :

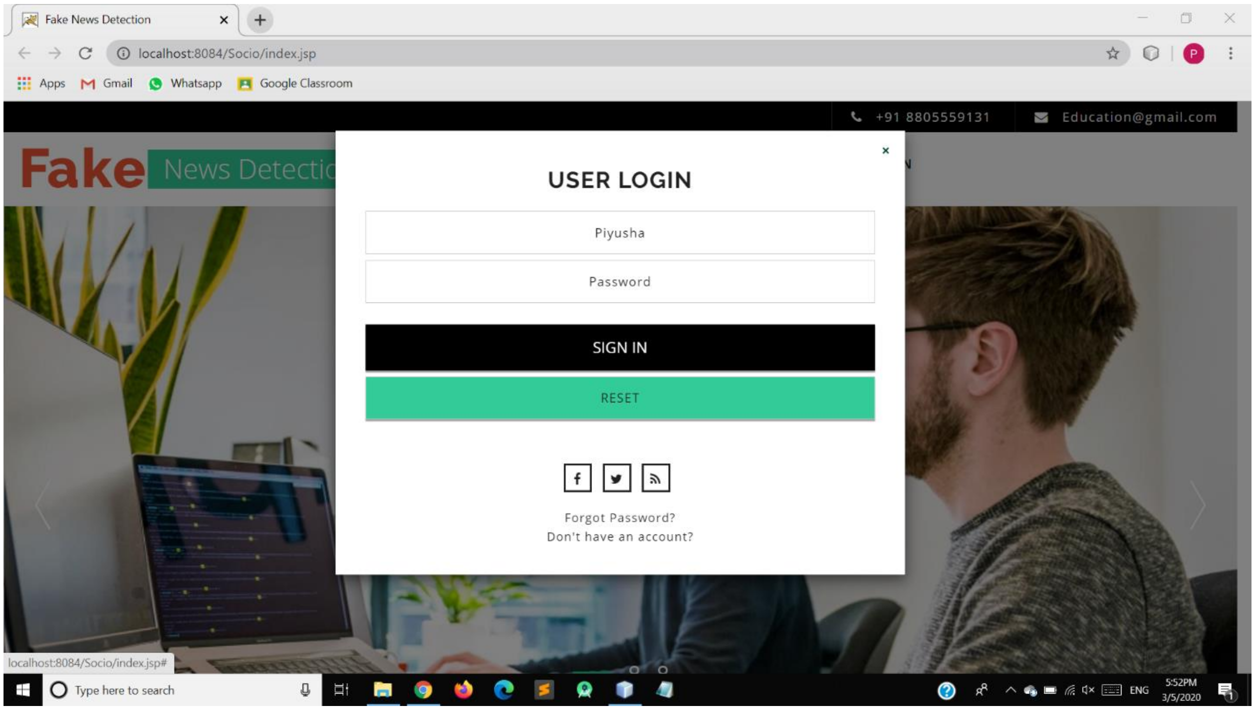
- Home : Having a banner of images.
- Admin Login : Tab from where admin can login.
- User Login : Tab from where only the registered user can login.
- User Registration : Tab from where a new user can register.



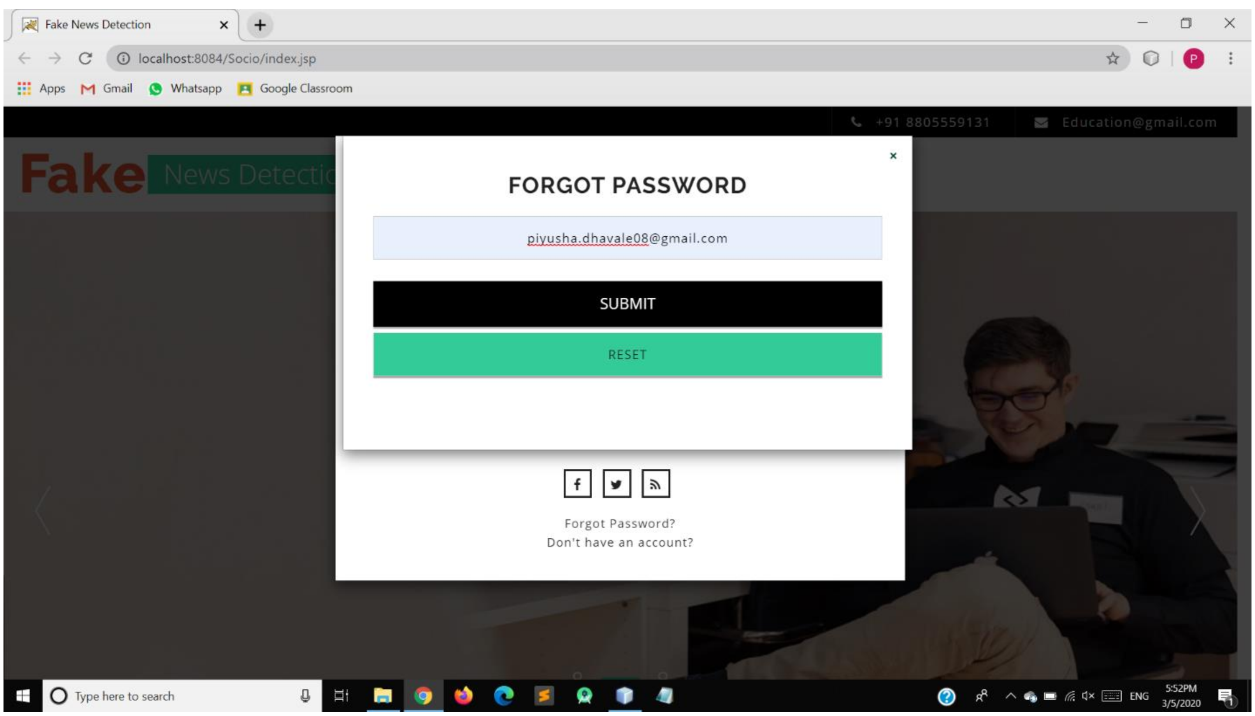
When you scroll the main page , introduction is available of the website



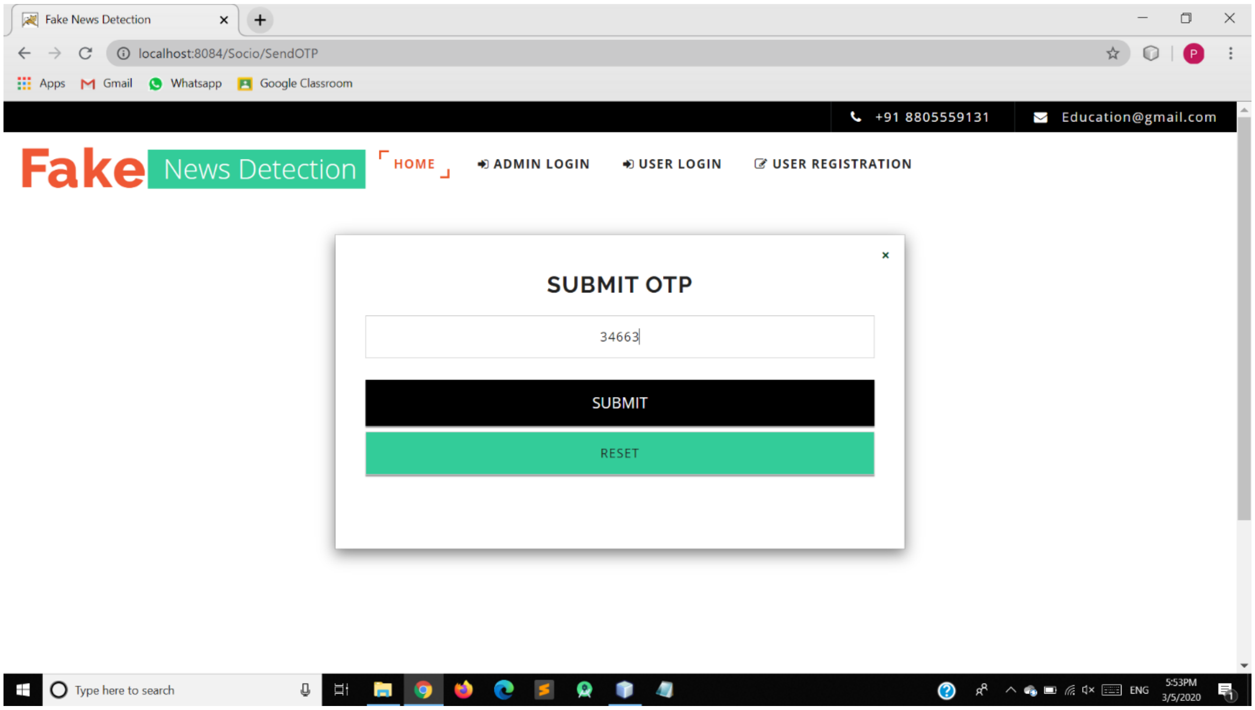
When clicked the "User Registration" tab user have to fill all the required information. Here validations are provided. It's not necessary for the user to have a twitter account. After filling the information, the user has to click the "Sign Up" button. The user gets registered to the database.



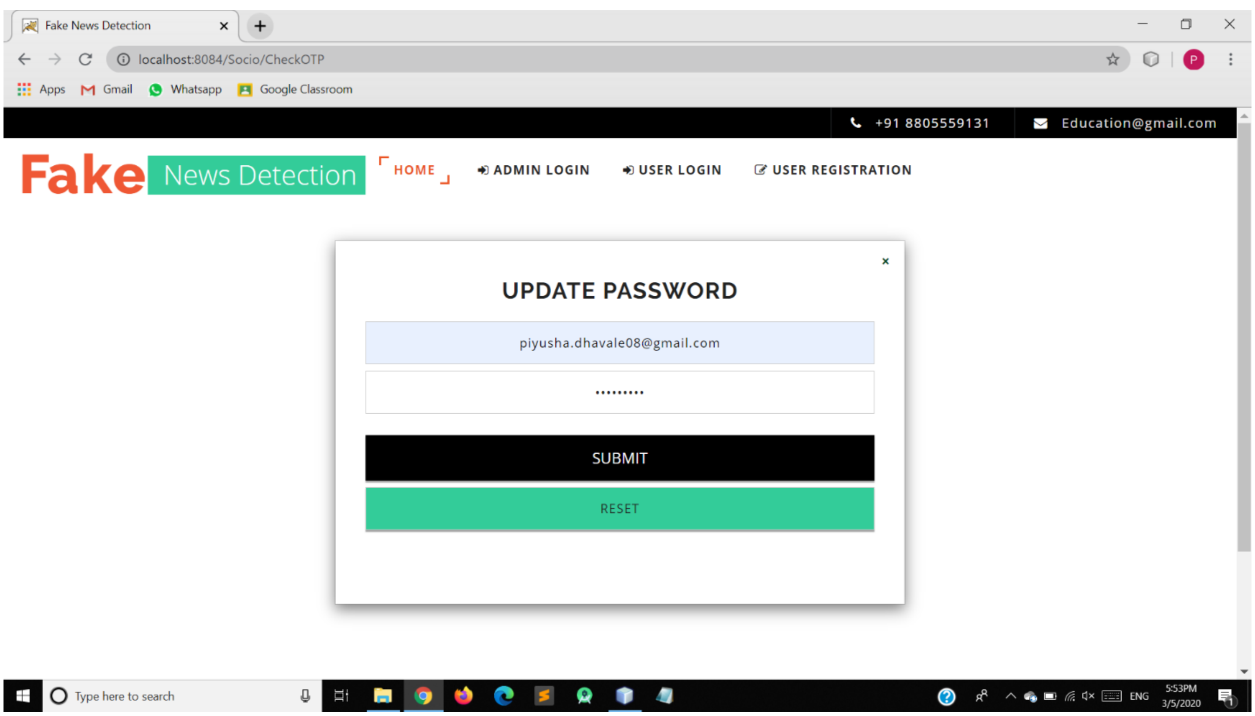
If the user forgets the password , click Forgot password.



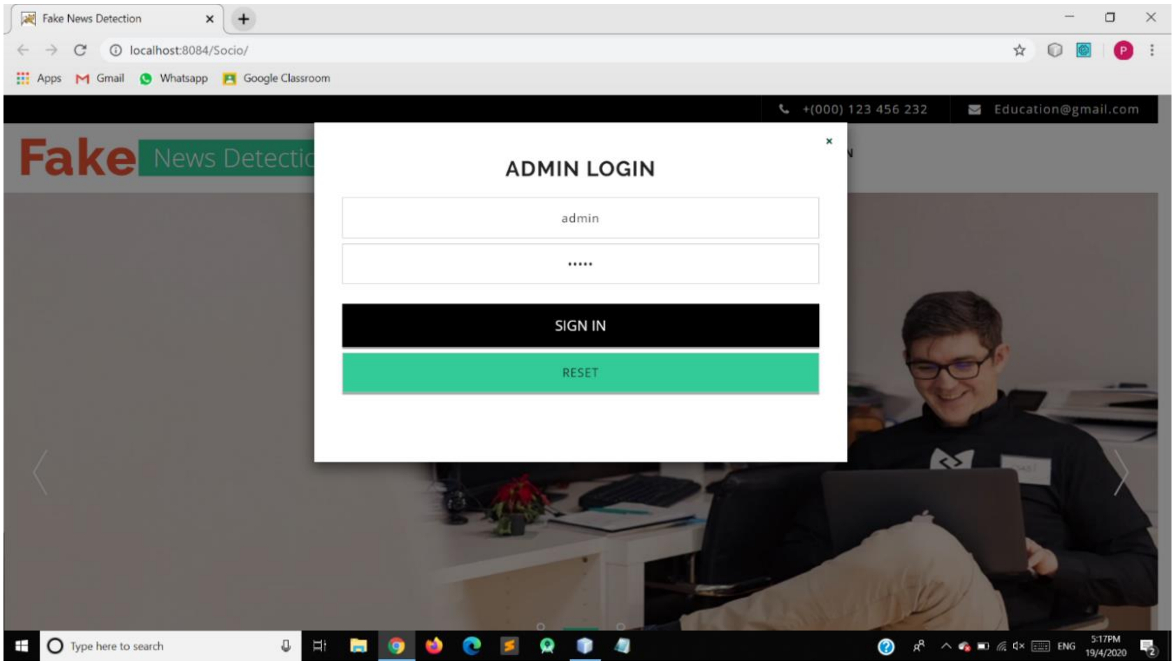
You have to enter your email address .



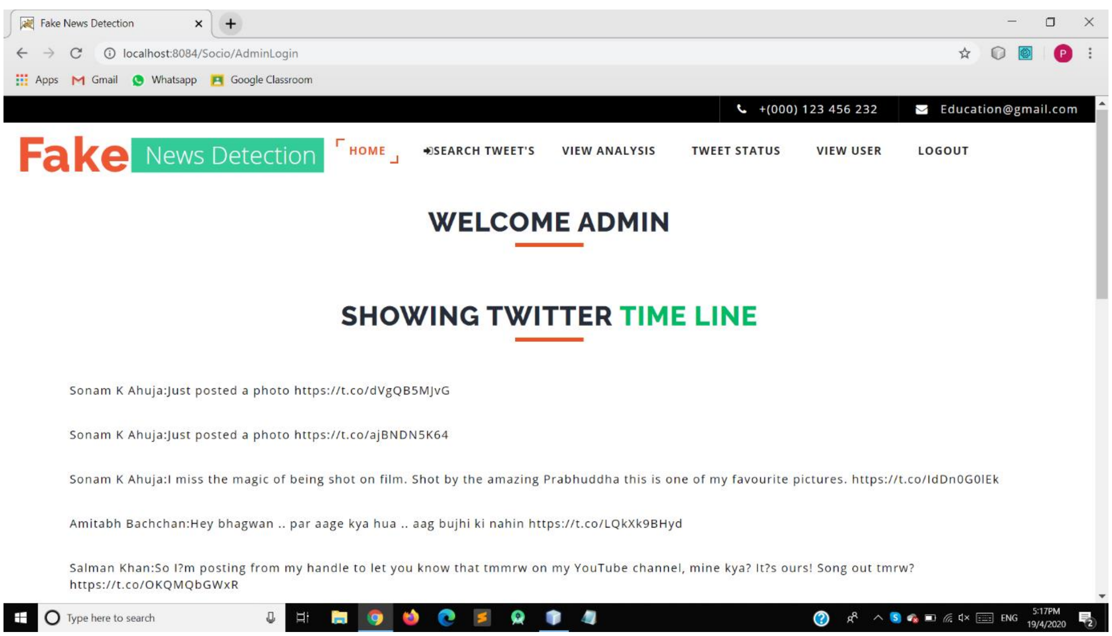
The OTP will be sent to your mobile number. You need to enter the OTP.



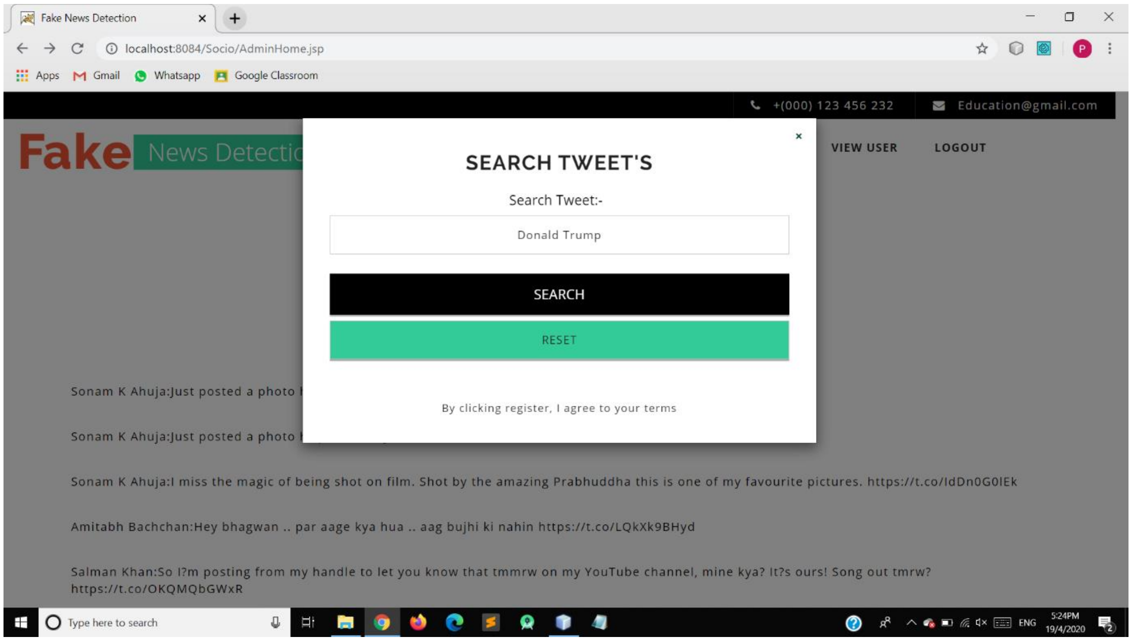
Update your password .



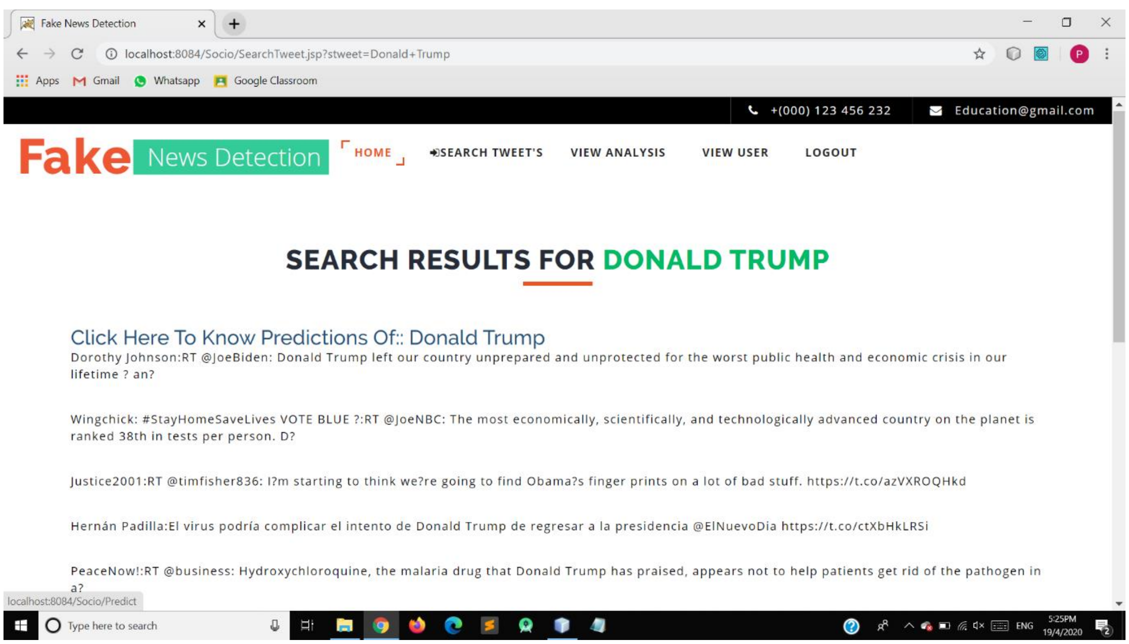
For the admin login, the admin just has to enter the username and the password and click the "Sign In" button.



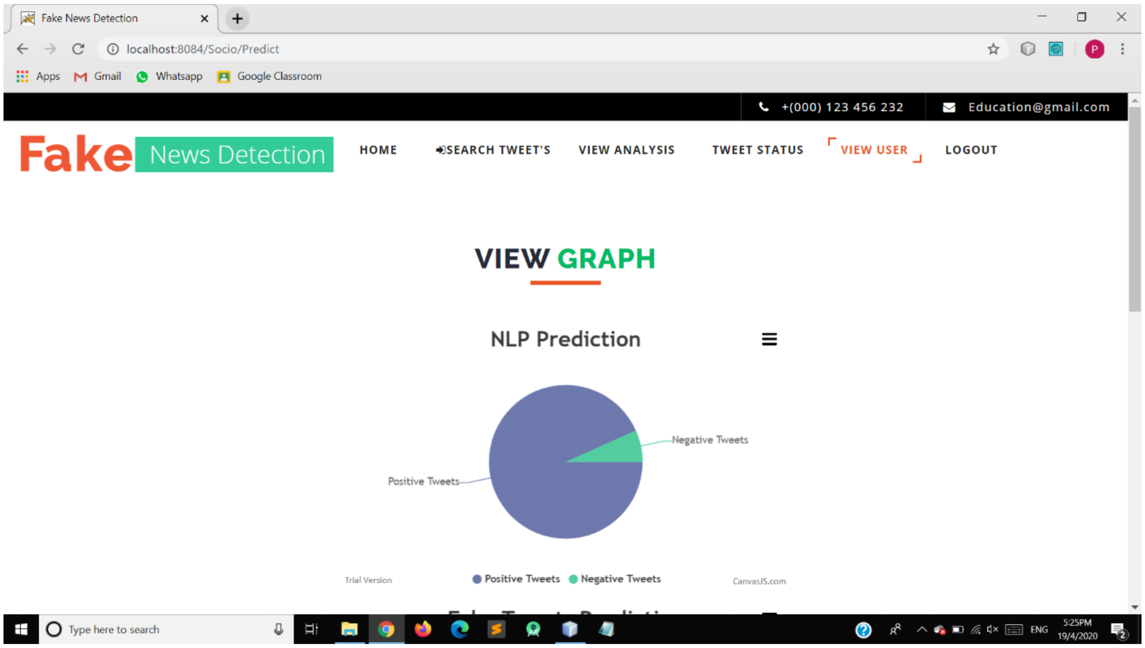
After admin login , this is the webpage seen. Here top 20 tweets from the admin twitter timeline are retrieved.



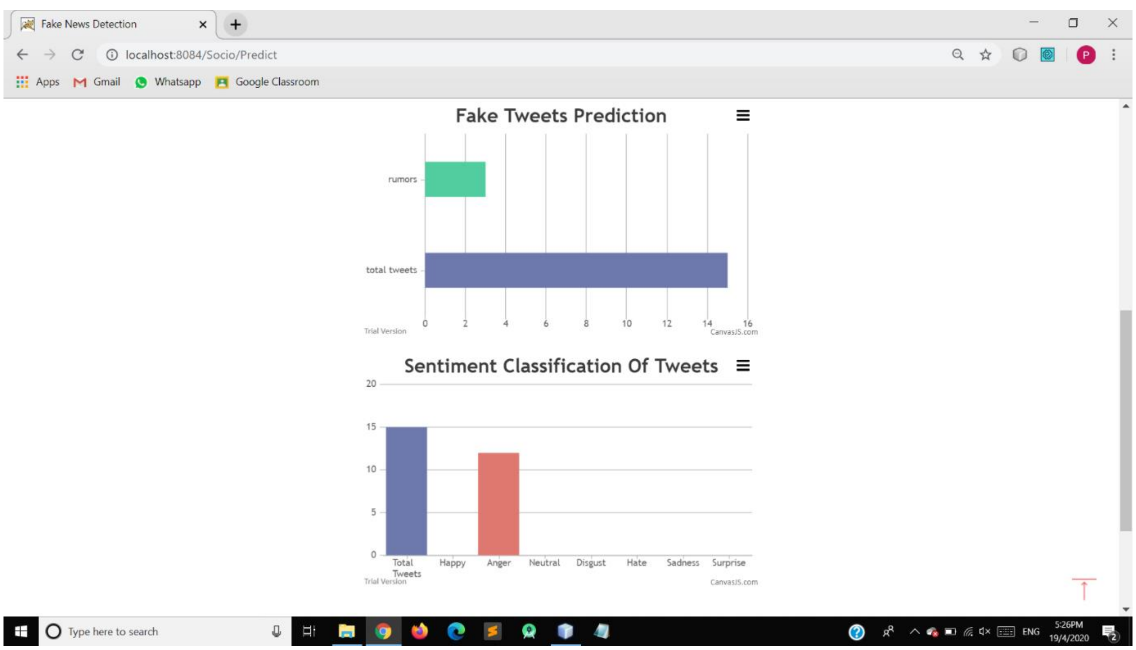
For searching tweets of a specific person, place, thing the admin needs to click the “Search Tweet’s” tab and enter the keyword (foreg. Donald Trump) and then click the “Search” button.



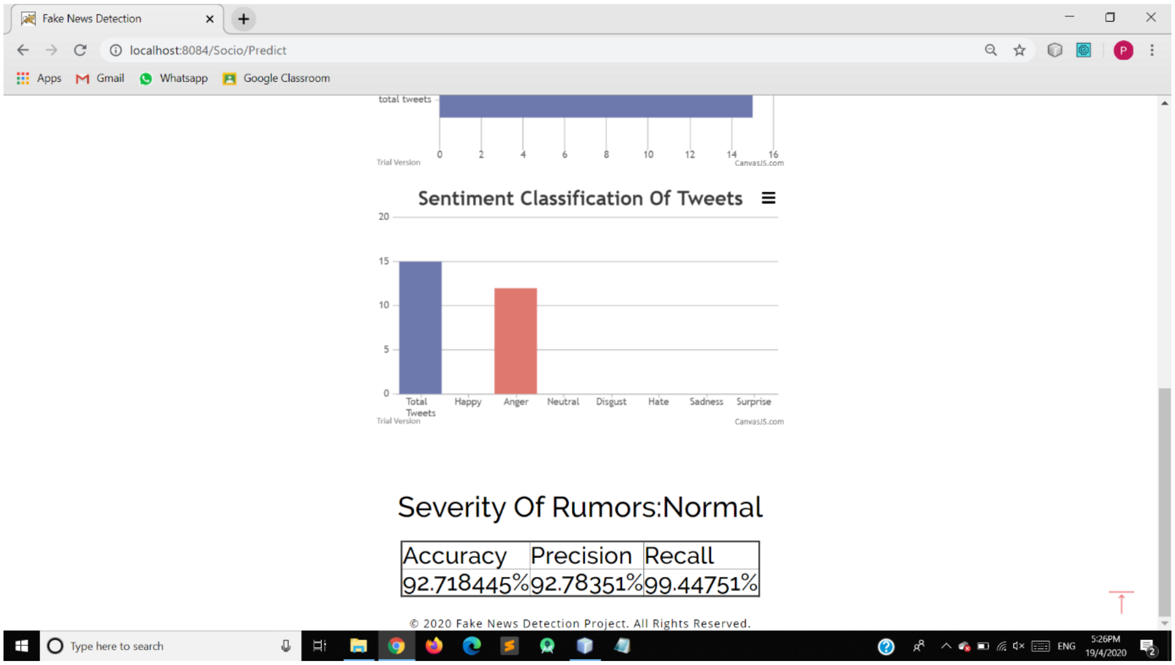
This is the webpage where top 20 tweets of the searched person are retrieved.



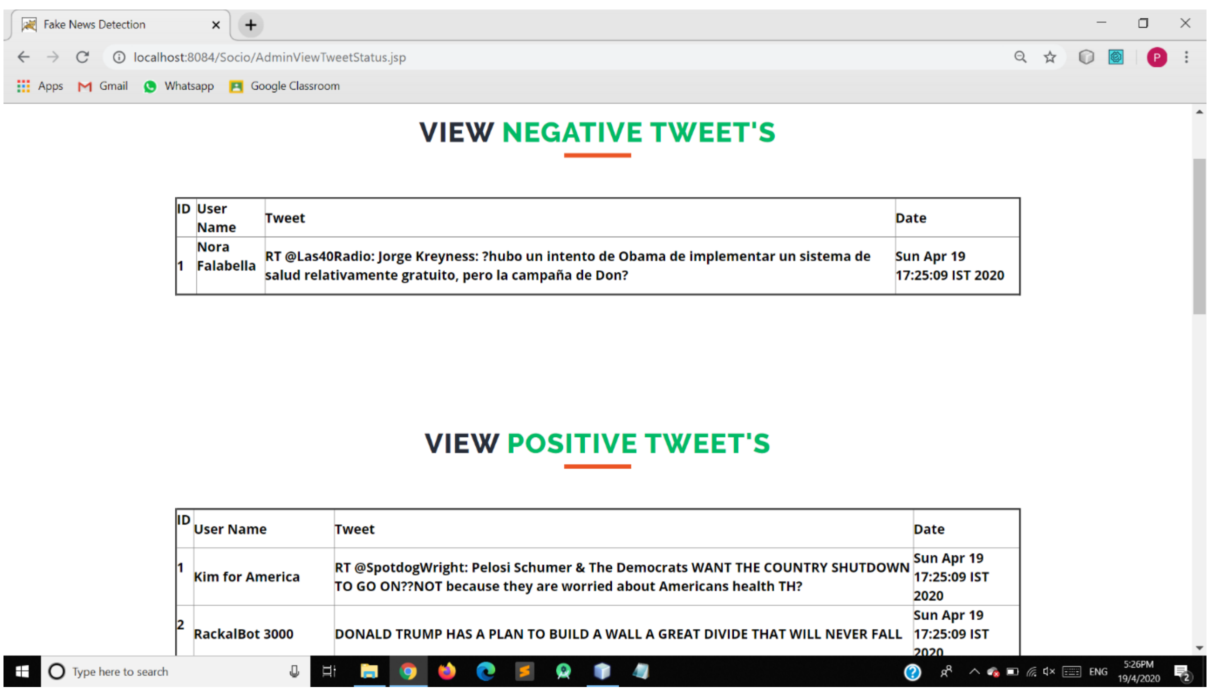
To know the Prediction of the searched person admin needs to click "Click here to know the Prediction". The admin gets redirected to a new webpage where using a PIE chart NLP prediction is shown.



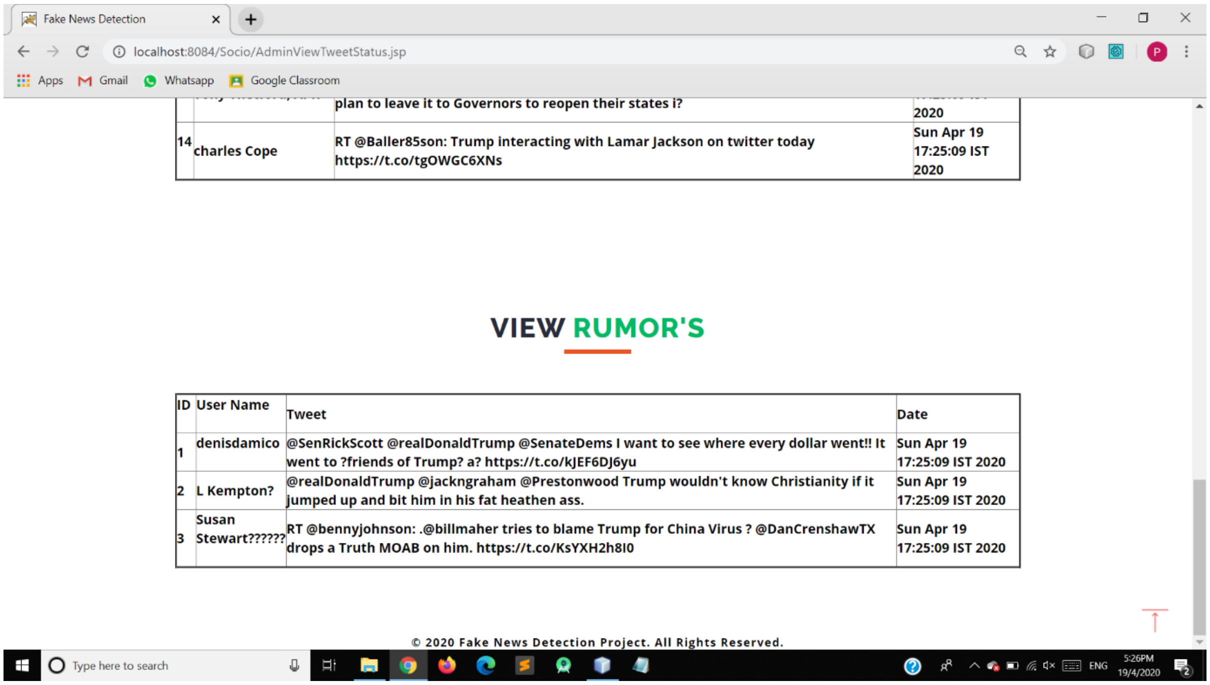
After scrolling the same webpage admin can have a look on the rumors and also sentimental analysis of the tweets.

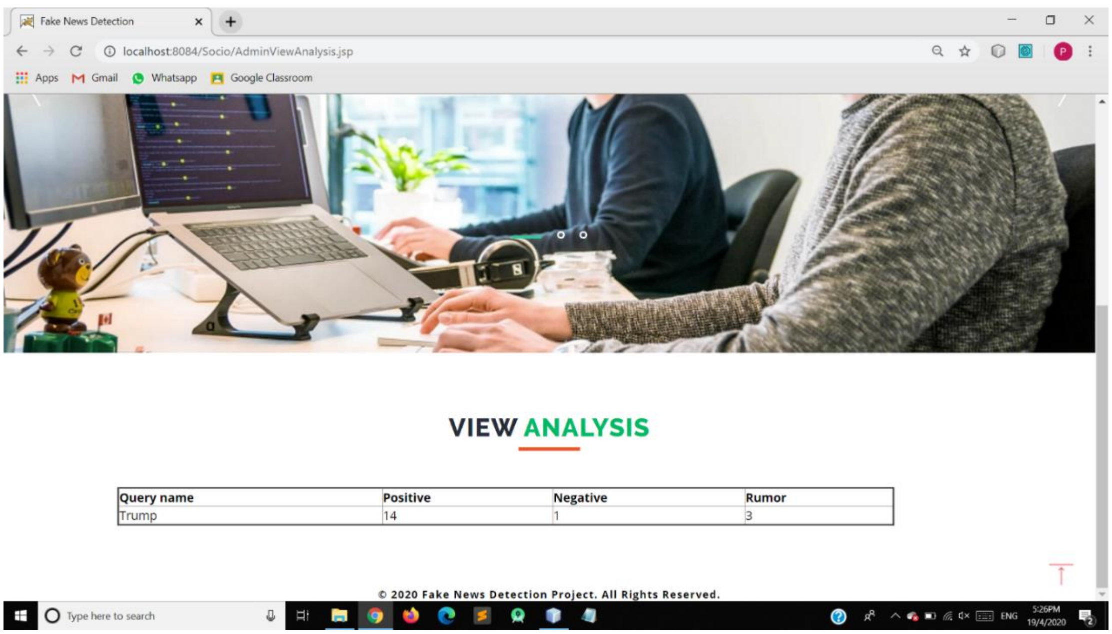


Admin can also have a look on the severity of rumors which are categorized as : low, normal and high.

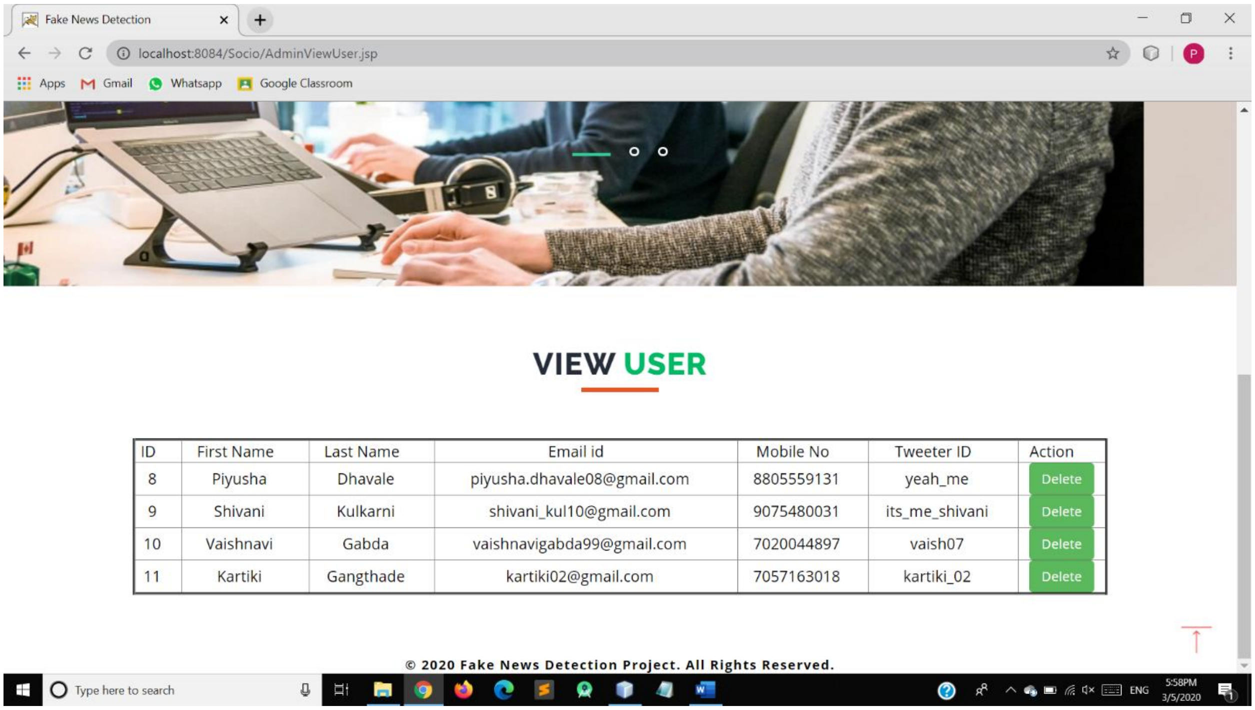


To view the tweet status , admin needs to click the “Tweet Status” tab where tweets are classified as Negative tweets, Positive tweets and Rumors.





By clicking on the "View Analysis" tab, the admin can have a look on the overall analysis of the tweets in a tabular format.



ID	First Name	Last Name	Email id	Mobile No	Tweeter ID	Action
8	Piyusha	Dhavale	piyusha.dhavale08@gmail.com	8805559131	yeah_me	Delete
9	Shivani	Kulkarni	shivani_kul10@gmail.com	9075480031	its_me_shivani	Delete
10	Vaishnavi	Gabda	vaishnavigabda99@gmail.com	7020044897	vaish07	Delete
11	Kartiki	Gangthade	kartiki02@gmail.com	7057163018	kartiki_02	Delete

By clicking on the “View User” tab , the admin can have a look on users registered.

8. CONCLUSION

The project set out to solve a practical problem of sentiment analysis and genuinely check of Twitter posts . We proposed a method using knowledge has patterns strategies and machine learning approaches. These methods are propsed to increase the accuracy of sentiment check for tweets.Patterns can be used to evaluate if the tweets was a influenced fake tweet or a genuine post by a user.

A method using knowledge A feature based identification system for rumor detection has been proposed. The approach treats user's behavior as hidden clues and uses three classifiers for training and testing purpose. Querying and fetching of particular tweets from twitter is possible by using its API. Finding influence or negativity spread by users can be useful in various analaytical tasks.

9. FUTURE SCOPE

- With the pervasiveness of online media data as a source of information, verifying the validity of this information is becoming even more important yet quite challenging.
- Rumors spread a large quantity of misinformation on microblogs.
- In this project we address two common issues within the context of microblog social media. First, we detect rumors as a type of misinformation propagation, and next, we go beyond detection to perform the task of rumor classification (RDC).
- We explore the problem using a standard data set. We devise novel features and study their impact on the task.
- We experiment with various levels of preprocessing as a precursor to the classification as well as grouping of features.
- We achieve an F-Measure of over 0.82 in the RDC task in a mixed rumors data set and 84% in a single rumor data set using a two step classification approach.
- With recent development of technology, especially mobile devices has made the social networks accessible 24/7.
- Information spreading has become faster than ever, regardless of the credibility of this information.
- This brings unparalleled challenges in ensuring the reliability of the information.
- Misinformation spreading has a strong relation especially in the context of breaking news, where the information released gradual, often starting as unverified information.
- Automatically identifying rumors from online social media especially micro-blogging websites is an important or everyone using it.
- Thus it has great scope in Future which helps in secure usage of social media .
- Finding influence or negativity spread by users can be useful in various analaytical tasks.

10.REFERENCES

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- https://ieeexplore.ieee.org/document/8058315
- https://www.javatpoint.com/jsp-tutorial
- https://www.tutorialspoint.com/jsp/index.htm
- https://www.youtube.com