A

MINI PROJECT REPORT

ON

TWITTER SENTIMENT ANALYSIS

Submitted in partial fulfilment of the requirement for the award of the degree of

BACHELOR OF TECHNOLOGY

IN

COMPUTER SCIENCE AND ENGINEERING

Submitted by

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Under the Guidance

Of

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TEEGALA KRISHNA REDDY ENGINEERING COLLEGE

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Medbowli, Meerpet, Saroornagar, Hyderabad – 500097

(Affiliated to JNTUH, Approved by AICTE, Accredited by NBA & NAAC 'A' grade)

(2021-2025)

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CERTIFICATE

This is to certify that the Mini Project report on **"TWITTER SENTIMENT ANALYSIS"** is a bonafide work carried out by **J.Jeevanth Kumar(21R91A0597)** in partial fulfillment for the requirement of the award of B.Tech degree in Computer Science and Engineering, Teegala Krishna Reddy Engineering College, Hyderabad, affiliated to Jawaharlal Nehru Technological University, Hyderabad under my guidance and supervision.

The result of investigation enclosed in this report have been verified and found satisfactory. The results embodied in the project work have not been submitted to any other University for the award of any degree.

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DECLARATION

We hereby declare that the Mini Project report entitled **"TWITTER SENTIMENT ANALYSIS"** is done under the guidance of **Mrs.Y. SHIVA SREE**, Assistant Professor**,** Department of Computer Science and Engineering, Teegala Krishna Reddy Engineering College, is submitted in partial fulfilment of the requirements for the award of the degree of **Bachelor of Technology in Computer Science and Engineering** from **Jawaharlal Nehru Technological University**, Hyderabad.

This is a record of bonfire work carried out by us in **Teegala Krishna Reddy Engineering College** and the results embodied in this project have not been reproduced or copied from any source.

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By

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ABSTRACT

Twitter sentiment analysis involves evaluating the sentiment expressed in tweets. The primary task is to classify tweets into sentiment categories, such as Positive or Negative. In this dataset, only textual data is used, with no numerical data involved. The analysis focuses on understanding public opinion and sentiment based on the textual content of tweets. The process starts with data pre-processing, which includes steps like tokenizing the text, converting it to lowercase, and removing punctuation, URLs, mentions, and hashtags. Stop words are eliminated, and techniques like lemmatization or stemming are applied to reduce words to their base forms. In this project, we will discuss the sentiment analysis of twitter dataset with data mining approach. An approach is introduced that automatically classifies the sentiments of Tweets taken from Twitter dataset by using different classifier algorithms. These tweets are classified as positive or negative along with the confidence. In this procedure of sentiment analysis, we will take the user input keyword and fetch the Live Twitter Data and classify them as positive and negative tweets and save them locally. The training and testing data consist of tweets which can be plain-text, acronyms and abbreviations.

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1. INTRODUCTION

Twitter sentiment analysis is a subfield of natural language processing (NLP) that involves analysing and determining the sentiment or emotional tone expressed in tweets. This task has become increasingly important as social media platforms like Twitter have grown to serve as real-time public forums for sharing opinions, news, and personal experiences. Since Twitter has a vast user base that actively engages in discourse on various topics, sentiment analysis on this platform offers insights into public opinion, consumer behaviour, political trends, and social issues.

Sentiment analysis on Twitter aims to classify tweets into categories such as positive, negative, or neutral. The importance of such analysis lies in its ability to provide a snapshot of public sentiment at any given moment. For example, businesses can use sentiment analysis to monitor customer feedback, politicians can gauge voter sentiment, and researchers can track societal moods related to specific events or issues. By understanding the general emotional tone of tweets, companies and organizations can make data-driven decisions, enhance customer experience, and improve their public relations strategies.

The complexity of Twitter sentiment analysis stems from the informal nature of the platform's language. Tweets often contain slang, abbreviations, emojis, and hashtags, which can make it challenging to accurately interpret the underlying sentiment. Furthermore, the brevity of tweets (limited to 280 characters) means that many tweets may lack the context necessary for precise sentiment classification. Irony, sarcasm, and mixed sentiments are common, further complicating the task. A tweet might express negative feelings about one aspect of a subject while praising another, which requires sophisticated models to interpret properly.

One of the primary techniques used in sentiment analysis is machine learning. Machine learning models can be trained on labelled datasets where tweets are tagged with sentiment labels, such as positive, negative, or neutral. These models learn to recognize patterns in the language used in tweets and can predict sentiment for unseen data. Some of

the most commonly used algorithms include support vector machines (SVM), random forests, and deep learning techniques such as recurrent neural networks (RNNs) and transformers. More recently, transformer-based models like BERT and GPT have shown great promise in improving the accuracy and performance of sentiment analysis tasks by capturing the nuanced relationships between words and their contextual meanings.

In addition to machine learning, lexicon-based methods are also used in sentiment analysis. These methods rely on predefined lists of words that are associated with positive or negative sentiment. For example, a lexicon may contain words like “happy” or “excited” which are considered positive, while words like “angry” or “disappointed” are considered negative. By counting the occurrence of positive and negative words in a tweet, these methods attempt to classify the sentiment of the text. While lexicon-based methods are relatively simple and interpretable, they may struggle to handle sarcasm, negations, and context-dependent sentiment. Therefore, combining machine learning with lexicon-based approaches is often a powerful strategy for sentiment analysis.

Despite advancements in sentiment analysis techniques, there are still significant challenges. One challenge is the handling of context and ambiguity in language. For instance, a tweet like “I love this product, but the service is terrible” expresses mixed sentiments that need to be separated for a meaningful analysis. Furthermore, the evolving nature of language, with the introduction of new slang and acronyms, requires continuous updates to the models and lexicons used for sentiment classification. The domain of a tweet also influences sentiment analysis—tweets about entertainment, politics, and technology, for example, may use different vocabulary and expressions that require domain-specific models.

The applications of Twitter sentiment analysis are vast. In the business world, companies monitor Twitter to detect customer satisfaction, identify potential problems, and track brand health. In politics, sentiment analysis can help understand voter behaviour, the popularity of political leaders, or the public's opinion on policy changes. During crises, such as natural disasters or pandemics, sentiment analysis can also provide real-time insights into public emotions and reactions, helping organizations respond effectively. witter sentiment analysis refers to the process of using natural language processing (NLP) and machine learning techniques to determine the emotional tone behind Twitter posts or

tweets. By analyzing the language used in tweets, sentiment analysis aims to classify them as positive, negative, or neutral, providing insights into public opinion on a specific topic, event, brand, or individual.

Twitter, with its vast user base and real-time nature, makes it an ideal platform for sentiment analysis. Tweets often express spontaneous reactions, opinions, and feelings, which can help gauge public sentiment on various subjects. The analysis can be performed at multiple levels, including individual tweets, trends, or hashtags.

Sentiment analysis on Twitter has various applications. In business, it helps brands monitor customer satisfaction and track the effectiveness of marketing campaigns. In politics, it provides insights into voter sentiment, while in crisis management, it helps track public reactions to ongoing events. However, challenges remain, including the handling of sarcasm, slang, and context-specific expressions, which can complicate accurate sentiment classification. Despite these challenges, Twitter sentiment analysis continues to be a valuable tool for understanding public sentiment in an increasingly connected and fast-paced world.

2. LITERATURE SURVEY

Sentiment Analysis is process of collecting and analysing data based upon the person feelings, reviews and thoughts. Sentimental analysis often called as opinion mining as it mines the important feature from people opinions. Sentimental Analysis is done by using various machine learning techniques, statistical models and Natural Language Processing (NLP) for the extraction of feature from a large data. Sentiment Analysis can be done at document, phrase and sentence level. In document level, summary of the entire document is taken first and then it is analyse whether the sentiment is positive, negative or neutral. In phrase level, analysis of phrases in a sentence is taken in account to check the polarity. In Sentence level, each sentence is classified in a particular class to provide the sentiment. Sentimental Analysis has various applications. It is used to generate opinions for people of social media by analysing their feelings or thoughts which they provide in form of text. Sentiment Analysis is domain centred, i.e. results of one domain cannot be applied to other domain. Sentimental Analysis is used in many real life scenarios, to get reviews about any product or movies, to get the financial report of any company, for predictions or marketing

Twitter is a micro blogging platform where anyone can read or write short form of message which is called tweets. The amount of data accumulated on twitter is very huge. This data is unstructured and written in natural language. Twitter Sentimental Analysis is the process of accessing tweets for a particular topic and predicts the sentiment of these tweets as positive or negative with the help of different machine learning algorithms.

The advancement of web technology and its growth, there is a huge volume of data present in the web for internet users and a lot of data is generated too.

Internet has become a platform for online learning, exchanging ideas and sharing opinions. Social networking sites like Twitter, Facebook, Google+ are rapidly gaining. There has been lot of work in the field of sentiment analysis of twitter data. This project focuses mainly on sentiment analysis of twitter data which is helpful to analyse the information in the tweets where opinions are highly unstructured, heterogeneous and are either positive or negative, or neutral in some cases.

Sentiment analysis can be defined as a process that automates mining of attitudes, opinions, views and emotions from text, speech, tweets and database sources through Natural Language Processing (NLP).

Sentiment analysis involves classifying opinions in text into categories like "positive" or "negative" or "neutral". It is also referred as subjectivity analysis, opinion mining, and appraisal extraction

The words opinion, sentiment, view and belief are used interchangeably but there are differences between them.

Python is a high level, dynamic programming language which is used for this thesis.Python3.4 version was used as it is a mature, versatile and robust programming version. It is an interpreted language which makes the testing and debugging extremely quickly as there is no compilation step. There are extensive open source libraries available for this version of python and a large community of users. Python is simple yet powerful, interpreted and dynamic programming language, which is well known for its functionality of processing natural language data, i.e. Spoken English using NLTK. Other high level programming languages such as 'R'and 'Mat lab' were considered because they have many benefits such as ease of use but they do not offer the same flexibility and freedom that Python can deliver. Python (Python 3.4) language is used as a programming platform for this twitter sentiment analysis.

Natural Language Toolkit (NLTK) is library in Python, which provides a base for building programs and classification of data. NLTK is a collection of resources for Python that can be used for text processing, classification, tagging and tokenization. This toolbox plays a key role in transforming the text data in the tweets into a format that can be used to extract sentiment from them.NLTK provides various functions which are used in pre-processing of data so that data available from twitter become fit for mining and extracting features

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3. SYSTEM ANALYSIS

3.1 EXISTING SYSTEM

Present system in use performs the sentiment analysis on offline data. Also, it is difficult for a common user to understand the end results of the sentiment. To overcome these difficulties, we came up with a project which is easy to use and produce simplified results for user understandability. Moreover, we targeted the popular micro blogging site – Twitter for best analysis.

Traditionally, sentiment analysis is done manually by reading and interpreting tweets. This process is time-consuming, prone to human bias, and not scalable for large datasets. Some existing tools use simple keyword-based approaches to classify sentiments. Generalized Machine Learning Models: Pre-built sentiment models may be used, but they may not be specifically trained on Twitter data, leading to less accurate results due to the unique language style of tweets.

Disadvantages:

1. DATA CAN BE MESSY AND INACCURATE
2. LOW EFFICIENCY

3.2 PROPOSED SYSTEM

The proposed system is as follows: The present proposed system targets day-to-day live streaming data so as to improve the accuracy of the sentiment about updated data. In our case, we targeted Twitter as our dataset. We take the live streaming tweets from twitter data and perform sentiment analysis.

This system takes the user input (a keyword) and fetch the live streaming twitter data. It performs the sentiment analysis on each and every tweet and generates sentiment value

Twitter-Specific Sentiment Analysis Model: The proposed system involves building a sentiment analysis model specifically trained on Twitter data, accounting for the platform's unique characteristics like hashtags, mentions, and abbreviations libraries The system automatically classifies tweets into positive or negative sentiments using natural

language processing (NLP) techniques. The system is capable of analyzing large datasets of tweets in real-time, providing timely insights, which is useful for monitoring trends and public opinions

Advantages:

1.HIGH ACCURACY

2.HIGH EFFICIENCY

3.3 SYSTEM REQUIREMENTS

HARDWARE

• SYSTEM	:	Core i3 12th generation
• RAM	:	4GB
• STORAGE	:	256GB
• HARD DISK	:	40GB

SOFTWARE

• OS	:	Windows 10/11
• PROGRAMMING LANGUAGES	:	Python

4. SYSTEM DESIGN

4.1 SYSTEM ARCHITECTURE

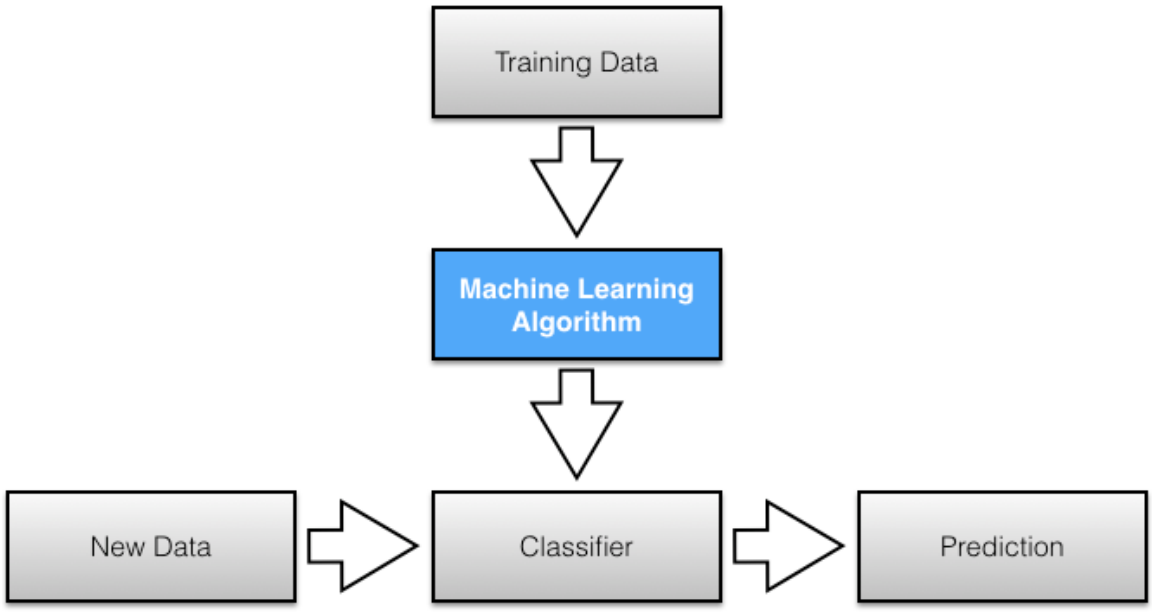


Fig.4.1: System Architecture

Explanation of System Architecture:

Prior to fitting the model and using machine learning algorithms for training, we need to think about how to best represent a text document as a feature vector. A commonly used model in Natural Language Processing is the so-called bag of words model. The idea behind this model really is as simple as it sounds. First comes the creation of the vocabulary — the collection of all different words that occur in the training set and each word is associated with a count of how it occurs. This vocabulary can be understood as a set of non-redundant items where the order doesn't matter.

Tokenization:

Tokenization describes the general process of breaking down a text corpus into individual elements that serve as input for various natural language processing algorithms. Usually, tokenization is accompanied by other optional processing steps, such as the removal of stop

words and punctuation characters, stemming or lemmatizing, and the construction of n-grams. Below is an example of a simple but typical tokenization step that splits a sentence into individual words, removes punctuation, and converts all letters to lowercase.

Stop Words:

Stop words are words that are particularly common in a text corpus and thus considered as rather un-informative (e.g., words such as so, and, or, the,"). One approach to stop word removal is to search against a language-specific stop word dictionary. An alternative approach is to create a stop list by sorting all words in the entire text corpus by frequency. The stop list — after conversion into a set of non-redundant words — is then used to remove all those words from the input documents that are ranked among the top n words in this stop list.

Stemming and Lemmatization:

Stemming describes the process of transforming a word into its root form. The original stemming algorithm was developed my Martin F. Porter in 1979 and is hence known as Porter stemmer. Stemming can create non-real words, such as "thus" in the example above. In contrast to stemming, lemmatization aims to obtain the canonical (grammatically correct) forms of the words, the so-called lemmas. Lemmatization is computationally more difficult and expensive than stemming, and in practice, both stemming and lemmatization have little impact on the performance of text classification.

Text Classification:

Salient The features are important and meaningful with respect to the problem domain One of the most important sub-tasks in pattern classification are feature extraction and selection; the three main criteria of good features are listed.

Invariance is often described in context of image classification: The features are insusceptible to distortion, scaling, orientation, etc. A nice example is given by C. Yao and others in Rotation-Invariant Features for Multi-Oriented Text Detection in Natural Images When a user requests information, the query is routed from the front-end to the backend database.

4.2 UML DIAGRAMS

The UML is a language for visualizing, specifying, constructing, documenting software systems and blueprints. There are several types of UML diagrams and each one of them serves a different purpose regardless of whether it is being designed before the implementation or after (as part of documentation). The two broadest categories that encompass all other types are Behavioural UML diagram and Structural UML diagram. As the name suggests, some UML diagrams try to analyze and depict the structure of a system or process, whereas others describe the behaviour of the system, its actors, and its building components. The different types are broken down as follows.

- Use Case Diagram
- Sequence Diagram
- Activity Diagram
- Collaboration

Just like any other thing in life, to get something done properly, you need the right tools. For documenting software, processes, or systems, you need the right tools that offer UML annotations and UML diagram templates. There are different software documentation tools that can help you draw a UML diagram. They are generally divided into these main categories: Paper and pen – this one is a no-brainer. Pick up a paper and a pen, open a UML syntax cheat sheet from the web and start drawing any diagram type you need. Online tools – there are several online applications that can be used to draw a UML diagram. Most of them offer free trials or a limited number of diagrams on the free tier. If you are looking for a long-term solution for drawing UML diagrams, it is generally more beneficial to buy a premium subscription for one of the applications.

4.2.1 USE CASE DIAGRAM

Use case diagrams are used to gather the requirements of a system including internal and external influences. A use case diagram at its simplest is a representation of a user's interaction with the system that shows the relationship between the user and the different use cases in which the user is involved. A use case diagram can identify the different types of users of a system and the different use cases and will often be accompanied by other types of diagrams as well.

These internal and external agents are known as actors. So use case diagrams consist of actors, use cases and their relationships. The diagram is used to model the

system/subsystem of an application. A single use case diagram captures a particular functionality of a system. So, to model the entire system numbers of use case diagrams are used.

Use case diagrams are used to gather the requirements of a system including internal and external influences. These requirements are mostly design requirements. So, when a system is analyzed to gather its functionalities, use cases are prepared and actors are identified. In brief, the purposes of use case diagrams can be as follows:

Used to gather requirements of a system.

Used to get an outside view of a system.

Identify external and internal factors influencing the system.

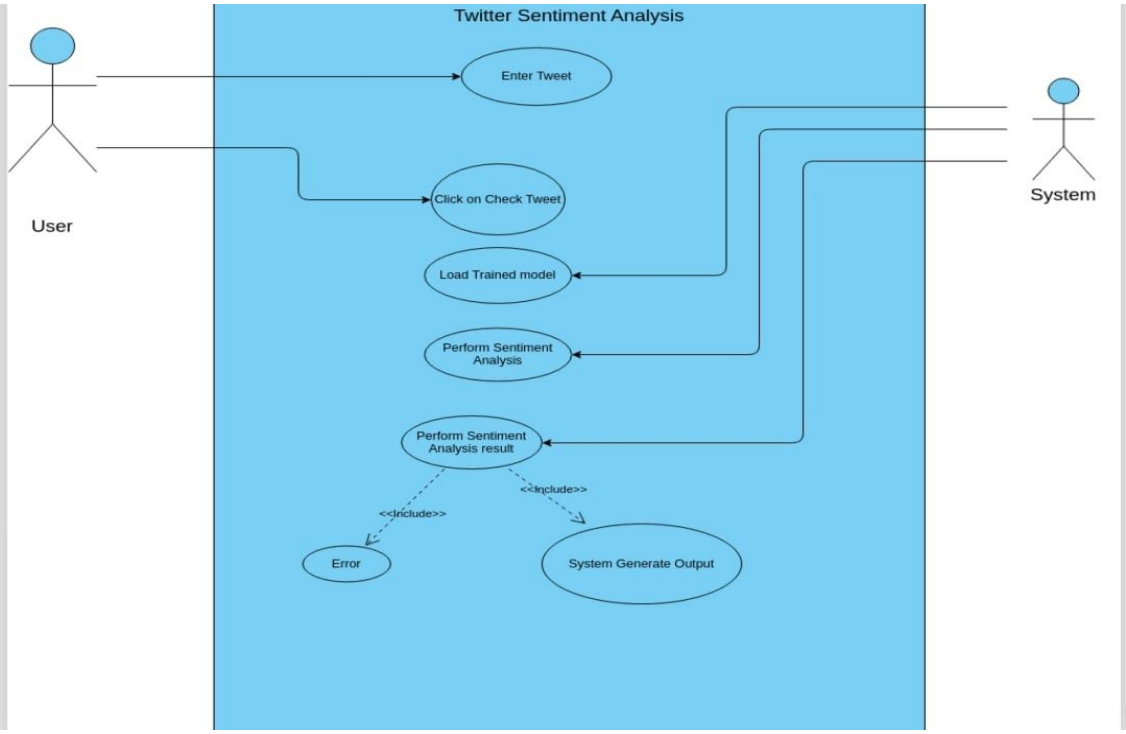


Fig 4.2.1: Use case Diagram

4.2.2 CLASS DIAGRAM

Class diagrams are the main building blocks of every object-oriented method. The class diagram can be used to show the classes, relationships, interface, association, and collaboration. UML is standardized in class diagrams. Since classes are the building block of an application that is based on OOPs, so as the class diagram has an appropriate structure to represent the classes, inheritance, relationships, and everything that OOPs have in their context. It describes various kinds of objects and the static relationship between them.

The main purpose to use class diagrams are:..

- It is based on deployment and component diagrams.

  Each class is represented by a rectangle having a subdivision of three compartments name, attributes operation.

  There are three types of modifiers which are used to decide the visibility of attributes and operations.

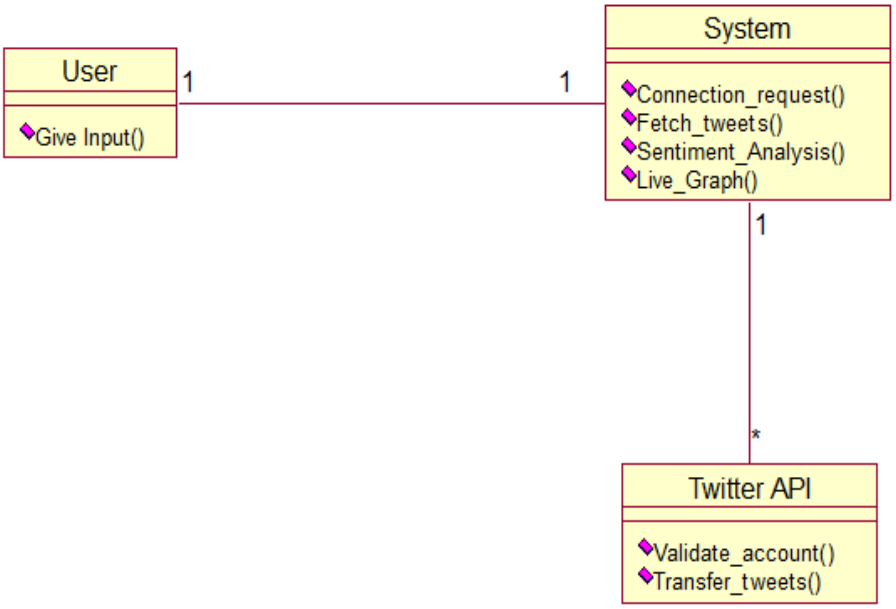


Fig 4.2.2: Class Diagram

4.2.3 SEQUENCE DIAGRAM

UML Sequence Diagrams are use to represent the flow of messages, events, and actions, between the objects or components of a system. Time is represented in the vertical direction showing the sequence of interactions of the header elements, which are displayed horizontally at the top of the diagram. Sequence Diagrams are used primarily to design, document and validate the architecture, interfaces and logic of the system by describing the sequence.

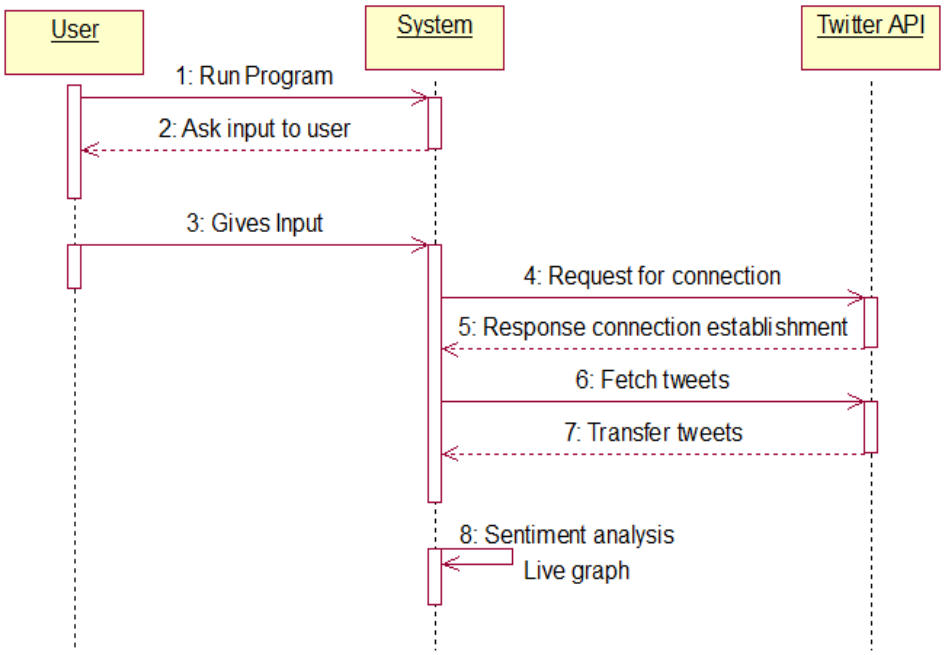


Fig4.2.3Sequence Diagram

actions that need to be performed to complete a task or scenario. UML sequence diagrams are useful design tools because they provide a dynamic view of the system behaviour which can be difficult to extract from static diagrams or specifications.

4.2.4 ACTIVITY DIAGRAM

Activity diagrams are graphical representations of workflows of stepwise activities and the actions with support for choice, iteration, and concurrency. In the UML, activity diagrams can be used to describe the business and operational step-by-step workflows of components in a system. An activity diagram shows the overall flow of control.

Each rectangular box represents an activity or action that occurs within the system. Arrows indicate the flow of control from one activity to another.

The diamond-shaped boxes represent decision points, where the flow of control may take different paths based on conditions.

The rounded rectangles represent the start and end points of the process.

Activity diagrams are graphical representations of workflows of stepwise activities and actions with support for choice, iteration and concurrency. In the Unified Modeling Language, activity diagrams can be used to describe the business and operational step-by-step workflows of components in a system. An activity diagram shows the overall flow of control.

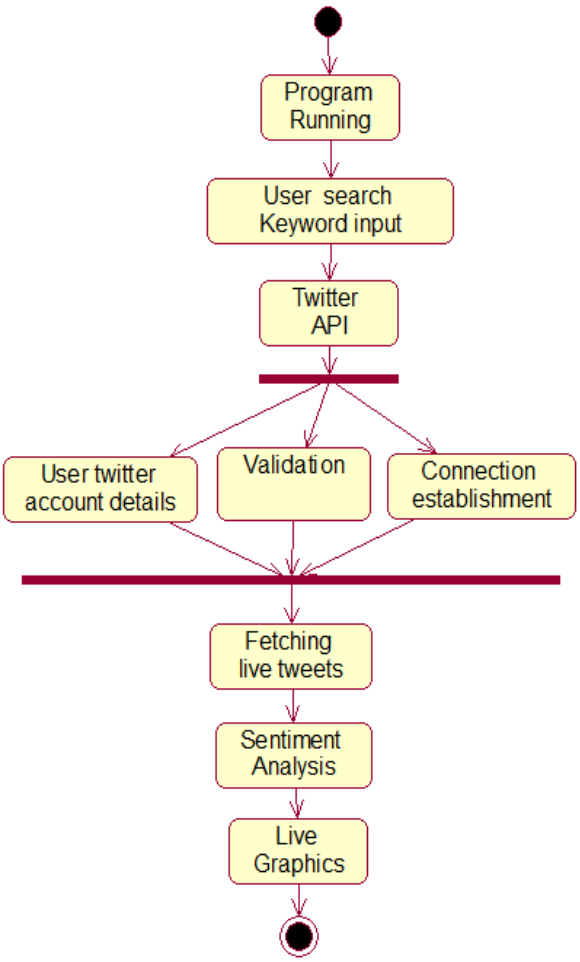


Fig 4.2.4: Activity Diagram

5. IMPLEMENTATION

5.1 INTRODUCTION

Working of the proposed system is as follows: The backend system consists of two important techniques web crawling and web scrapping. Web scrapping is a technique that is used to extract information in the human readable format and display it on destination terminal. But before scrapping the output, Web Crawlers are responsible to navigate to the destination once the crawler reaches the correct page and matches up with the products, scrapping process starts. Web scrapping essentially consists of two tasks: first is to load the desired web page and second is to parse HTML information of the page to locate intended information. In this system Scrapping is done using python as it provides rich set of libraries to address these tasks. “requests” is used to load the URLs and “Beautiful soup” library is used to parse the web page. After scrapping the products information from different e-commerce websites, the data is displayed on the website. The website is designed using flask web framework which is written in python. Required results are retrieved and displayed on Main website. The client can then compare prices of products that are available on e-commerce websites.

5.2 Install Python Step-by-Step in Windows and Mac :

Python a versatile programming language doesn’t come pre-installed on your computer devices. Python was first released in the year 1991 and until today it is a very popular high-level programming language. Its style philosophy emphasizes code readability with its notable use of great white space. The object-oriented approach and language construct provided by Python enables programmers to write both clear and logical code for projects. This software does not come pre-packaged with Windows.

How to Install Python on Windows and Mac :

There have been several updates in the Python version over the years. The question is how to install Python? It might be confusing for the beginner who is willing to start learning Python but this tutorial will solve your query. The latest or the newest version of Python is version 3.9.0 or in other words, it is Python 3.

Note: The python version 3.9.0 cannot be used on Windows XP or earlier devices. Before you start with the installation process of Python. First, you need to know about your **System Requirements**. Based on your system type i.e. operating system and based processor, you must download the python version. My system type is a **Windows 64-bit operating system**. So the steps below are to install python version 3.9.0 on Windows 11 device or to install

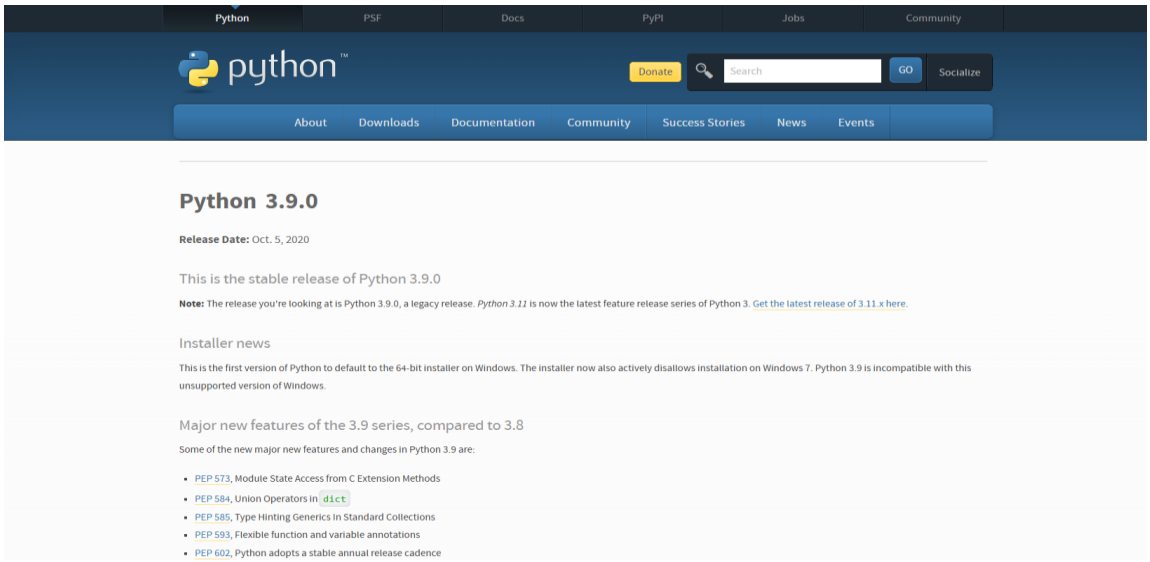
Python 3. Download the Python Cheat sheet here.The steps on how to install Python on Windows 10, 8 and 7 are **divided into 4 parts** to help understand better.

Download the Correct version into the system

Step 1: Go to the official site to download and install python using Google Chrome or any other web browser. OR Click on the following link: https://www.python.org.

Now, check for the latest and the correct version for your operating system.

Step2: Click on the Download Tab



Step 3: You can either select the Download Python for windows 3.9.0 button in Yellow Color or you can scroll further down and click on download with respective to their version. Here, we are downloading the most recent python version for windows 3.9.0

Active Python Releases

For more information visit the Python Developer's Guide.

Python version	Maintenance status	First released	End of support	Release schedule
3.14	pre-release	2025-10-01 (planned)	2030-10	PEP 745
3.13	bugfix	2024-10-07	2029-10	PEP 719
3.12	bugfix	2023-10-02	2028-10	PEP 693
3.11	security	2022-10-24	2027-10	PEP 664
3.10	security	2021-10-04	2026-10	PEP 619
3.9	security	2020-10-05	2025-10	PEP 596
3.8	end of life, last release was 3.8.20	2019-10-14	2024-10-07	PEP 569

Step 4: Scroll down the page until you find the Files option.

Step 5: Here you see a different version of python along with the operating system.

Files

Version	Operating System	Description	MD5 Sum	File Size	GPG
Gzipped source tarball	Source release		e19e75ec81dd04de27797bf3f9d918fd	25.5 MB	SIG
XZ compressed source tarball	Source release		6ebfe157f6e88d9eabfbaf3fa92129f6	18.0 MB	SIG
macOS 64-bit installer	macOS	for OS X 10.9 and later	16ca86fa3467e75bade26b8a9703c27f	29.7 MB	SIG
Windows help file	Windows		9ea6fc676f0fa3b95af3c5b3400120d6	8.4 MB	SIG
Windows x86 embeddable zip file	Windows		d81fc534080e10bb4172ad7ae3da5247	7.2 MB	SIG
Windows x86 executable installer	Windows		4a2812db8ab9f2e522c96c7728cfcccb	25.8 MB	SIG
Windows x86 web-based installer	Windows		cdbfa799e6760c13d06d0c2374110aa3	1.3 MB	SIG
Windows x86-64 embeddable zip file	Windows	for AMD64/EM64T/x64	60d0d94337ef657c2cca1d3d9a6dd94b	8.0 MB	SIG
Windows x86-64 executable installer	Windows	for AMD64/EM64T/x64	b61a33dc28f13b561452f3089c87eb63	26.9 MB	SIG
Windows x86-64 web-based installer	Windows	for AMD64/EM64T/x64	733df85afb160482c5636ca09b89c4c8	1.3 MB	SIG

• To download Windows 32-bit python, you can select any one from the three options: Windows x86 embeddable zip file, Windows x86 executable installer or Windows x86 web-based installer.

•To download Windows 64-bit python, you can select any one from the three options: Windows x86-64 embeddable zip file, Windows x86-64 executable installer or Windows x86-64 web-based installer. Here we will install Windows x86-64 web-based installer. Here your first part regarding which version of python is to be downloaded is completed. Now we move ahead with the second part in installing python i.e. Installation

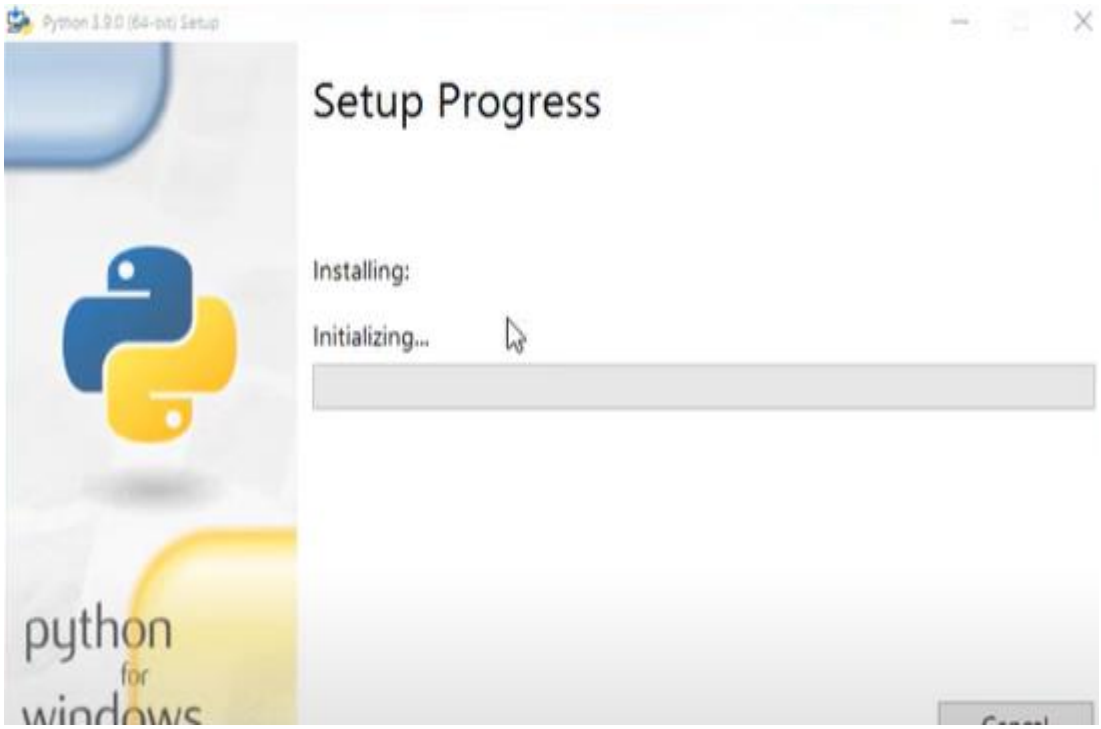
Note: To know the changes or updates that are made in the version you can click on the Release Note Option.

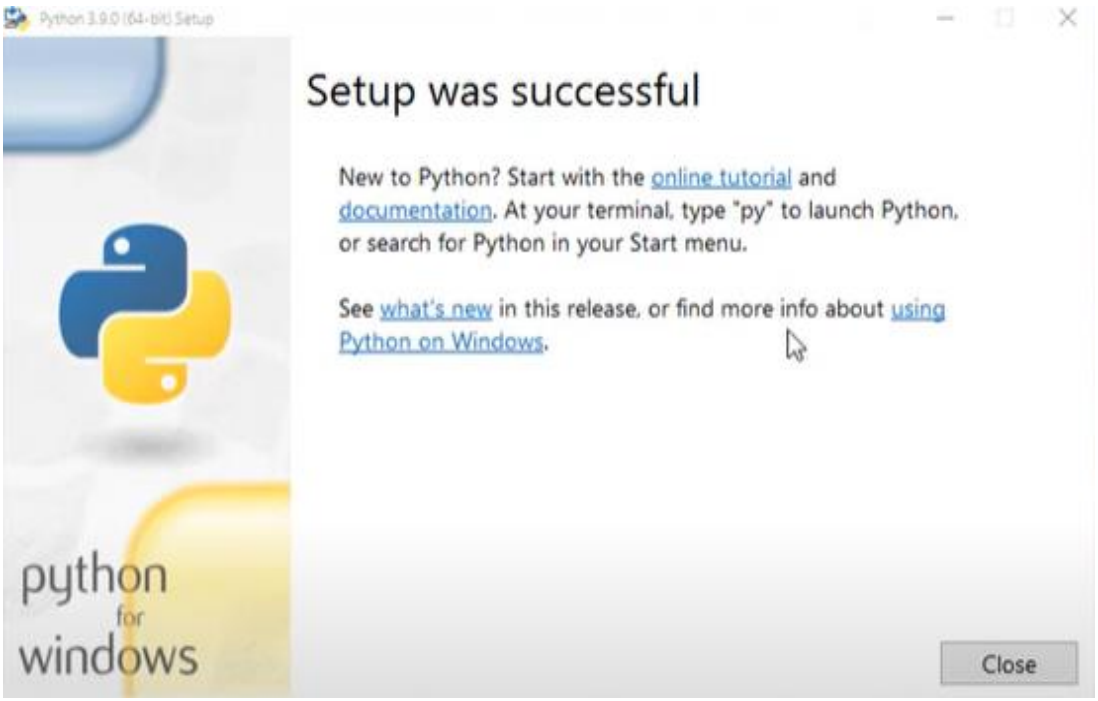
Installation of Python

Step 1: Go to Download and Open the downloaded python version to carry out the installation process

Before you click on Install Now, Make sure to put a tick on Add Python 3.9.0 to PATH

Step 2: Click on Install NOW After the installation is successful. Click on Close.





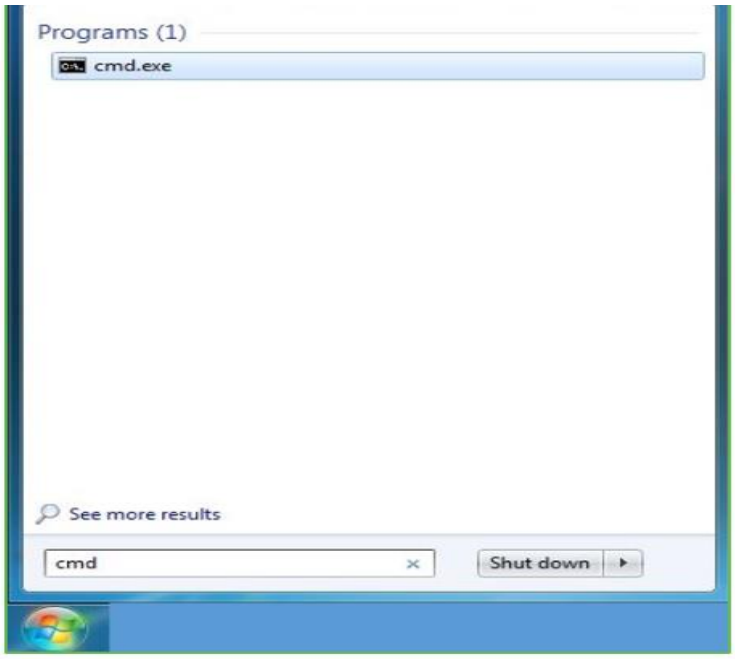
With these above three steps on python installation, you have successfully and correctly installed Python. Now is the time to verify the installation.

Note: The installation process might take a couple of minutes.

Verify the Python Installation

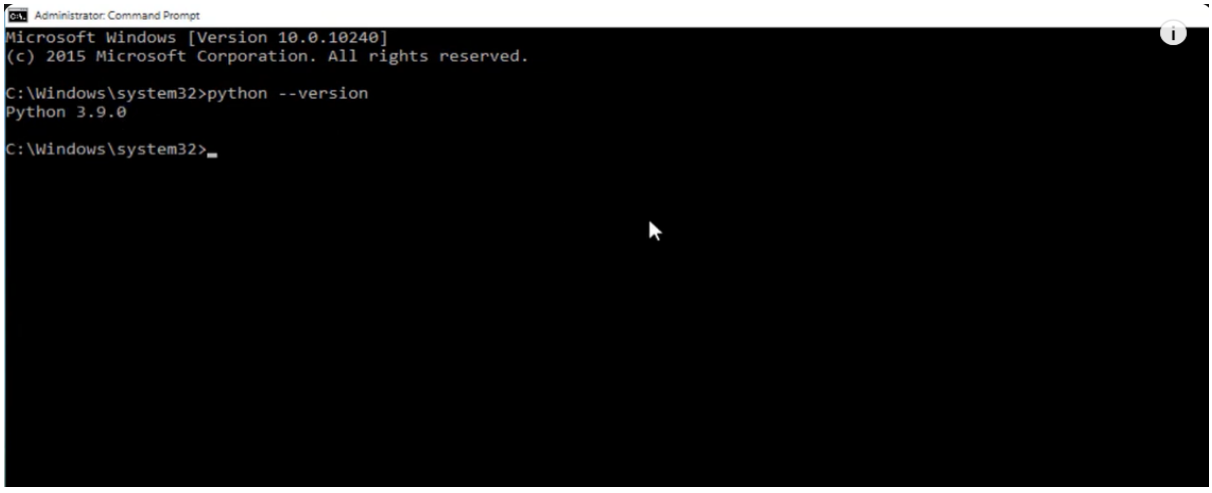
Step 1: Click on Start

Step 2: In the Windows Run Command, type “cmd”.



Step 3: Open the Command prompt option.

Step 4: Let us test whether the python is correctly installed. Type **python –V** and press Enter



Step 5: You will get the answer as 3.9.0

Note: If you have any of the earlier versions of Python already installed. You must first uninstall the earlier version and then install the new one.

6. CODING

```
#!/usr/bin/env python
# coding: utf-8
# # Twitter Sentiment Analysis with Random Forest
# ## What is Sentiment Analysis?
# Sentiment Analysis is the process of ‘computationally’ determining whether a piece of writing is positive, negative or neutral. It’s also known as opinion mining, deriving the opinion or attitude of a speaker.
# ![image.png](attachment:image.png)
# ## Lets Start Coding
# In[1]:
# load the dataset -> feature extraction -> data visualization -> data cleaning -> train test split
# -> model building -> model training -> model evaluation -> model saving -> streamlit application deploy
# disable warning
import warnings
warnings.filterwarnings('ignore')
import pandas as pd
df = pd.read_csv('https://raw.githubusercontent.com/laxmimerit/All-CSV-ML-Data-Files-Download/master/twitter_sentiment.csv', header=None, index_col=[0])
df = df[[2,3]].reset_index(drop=True)
df.columns = ['sentiment', 'text']
df.head()
# In[2]:
df.info()
df.isnull().sum()
df.dropna(inplace=True)
df = df[df['text'].apply(len)>1]
```

```
# In[3]:
df['sentiment'].value_counts()
# In[5]:
df.columns
# In[6]:
# Data Visualization
import matplotlib.pyplot as plt
import seaborn as sns
# plot 2x4 grid histogram for each numerical feature
plt.figure(figsize=(20,10))
num_cols = df.select_dtypes(include='number').columns
for col in num_cols:
    plt.subplot(2,4, num_cols.get_loc(col)+1)
    # use sentiment as hue to see the distribution of each numerical feature
    # sns.distplot(df[col], label=col, color='red')
    # sns.histplot(x=col, hue='sentiment', data=df, color='green', bins=100, kde=True)
    sns.kdeplot(data=df, x=col, hue='sentiment', fill=True)
# In[7]:
df['sentiment'].value_counts().plot(kind='pie', autopct='%1.0f%%')
# word cloud
from wordcloud import WordCloud, STOPWORDS
stopwords = set(STOPWORDS)
# In[8]:
# plot 2x2 grid word cloud for each sentiment
plt.figure(figsize=(40,20))
for index, col in enumerate(df['sentiment'].unique()):
    plt.subplot(2,2, index+1)
    # print(col)
    df1 = df[df['sentiment']==col]
    data = df1['text']
    wordcloud = WordCloud(background_color='white', stopwords=stopwords,
max_words=500, max_font_size=40, scale=5).generate(str(data))
```

```
    # fig = plt.figure(figsize=(15,15))
    # plt.axis('off')
    # disable ticks
    plt.xticks([])
    plt.yticks([])
    plt.imshow(wordcloud)
    plt.title(col, fontsize=40)
plt.show()
plt.tight_layout()
# In[14]:
import re
def lower(x):
    return x.str.lower()
def html(x):
    return x.apply(lambda x:re.sub("<.+?>"," ",x))
def url(x):
    return x.apply(lambda x:re.sub("[.+]?http[s]?://.+? +"," ",x))
def unw(x):
    return x.apply(lambda x:re.sub("[]\?:()*\-.!,@#$%^&0-9]"," ",x))
# In[15]:
df['text'] = lower(df['text'])
df['text'] = html(df['text'])
df['text'] = url(df['text'])
df['text'] = unw(df['text'])
# In[16]:
# train test split
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(df['text'], df['sentiment'], test_size=0.2,
random_state=42)
# In[17]:
X_train.shape, X_test.shape
# In[18]:
```

```
# model building
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.ensemble import RandomForestClassifier
from sklearn.pipeline import Pipeline
clf = Pipeline([('tfidf', TfidfVectorizer(stop_words=stopwords)), ('clf',
RandomForestClassifier(n_estimators=100, n_jobs=-1))])
clf.fit(X_train, y_train)
# evaluation
from sklearn.metrics import accuracy_score
predictions = clf.predict(X_test)
print(accuracy_score(y_test, predictions))
# save model
#import pickle
#pickle.dump(clf, open('twitter_sentiment.pkl', 'wb'))

# install streamlit: pip install streamlit
# run: streamlit run app.py
import streamlit as st
import pickle
import time
# load the model
model = pickle.load(open('twitter_sentiment.pkl', 'rb'))
st.title('Twitter Sentiment Analysis')
tweet = st.text_input('Enter your tweet')
submit = st.button('Predict')
if submit:
    start = time.time()
    prediction = model.predict([tweet])
    end = time.time()
    st.write('Prediction time taken: ', round(end-start, 2), 'seconds')
        print(prediction[0])
    st.write(prediction[0])
```

7. SYSTEM TESTING

The purpose of testing is to discover errors. Testing is the process of trying to discover every conceivable fault or weakness in a work product. It provides a way to check the functionality of components, sub-assemblies, assemblies and/or a finished product It is the process of exercising software with the intent of ensuring that the Software system meets its requirements and user expectations and does not fail in an unacceptable manner. There are various types of tests. Each test type addresses a specific testing requirement.

TYPES OF TESTING

Unit testing

Unit testing involves the design of test cases that validate that the internal program logic is functioning properly, and that program inputs produce valid outputs. All decision branches and internal code flow should be validated. It is the testing of individual software units of the application .it is done after the completion of an individual unit before integration. This is a structural testing, that relies on knowledge of its construction and is invasive. Unit tests perform basic tests at component level and test a specific business process, application, and/or system configuration. Unit tests ensure that each unique path of a business process performs accurately to the documented specifications and contains clearly defined inputs and expected results.

Integration testing

Integration tests are designed to test integrated software components to determine if they run as one program. Testing is event driven and is more concerned with the basic outcome of screens or fields. Integration tests demonstrate that although the components were individually satisfaction, as shown by successfully unit testing, the combination of components is correct and consistent. Integration testing is specifically aimed at exposing the problems that arise from the combination of components.

Functional testing

Functional tests provide systematic demonstrations that functions tested are available as specified by the business and technical requirements, system documentation, and user manuals. Functional testing is centered on the following items:

- Valid Input: identified classes of valid input must be accepted.
- Invalid Input: identified classes of invalid input must be rejected.
- Functions: identified functions must be exercised.
- Output: identified classes of application outputs must be exercised.
- Systems/Procedures: interfacing systems or procedures must be invoked.

Organization and preparation of functional tests is focused on requirements, key functions, or special test cases. In addition, systematic coverage pertaining to identify Business process flows; data fields, predefined processes, and successive processes must be considered for testing. Before functional testing is complete, additional tests are identified and the effective value of current tests is determined.

System testing

System testing ensures that the entire integrated software system meets requirements. It tests a configuration to ensure known and predictable results. An example of system testing is the configuration- o r i e n t e d system integration test. System testing is based on process descriptions and flows, emphasizing pre-driven process links and integration points.

White Box testing

White Box Testing is a test in which the software tester has knowledge of the inner workings, structure, and language of the software, or at least its purpose. It is purpose. It is used to test areas that cannot be reached from a black box level.

Black Box testing

Black Box Testing is testing the software without any knowledge of the inner workings, structure or language of the module being tested. Black box tests, as most other kinds of tests, must be written from a definitive source document, such as specification or requirements.

Performance Testing:

is the testing to assess the speed and effectiveness of the system and to make sure it is generating results within a specified time as in performance requirements. Our present system with 4GB RAM capacity can give decent performance of streaming live data. However, it undergoes degradation after streaming average of 1300 tweets.

8. OUTPUT SCREENS

INTERFACE:

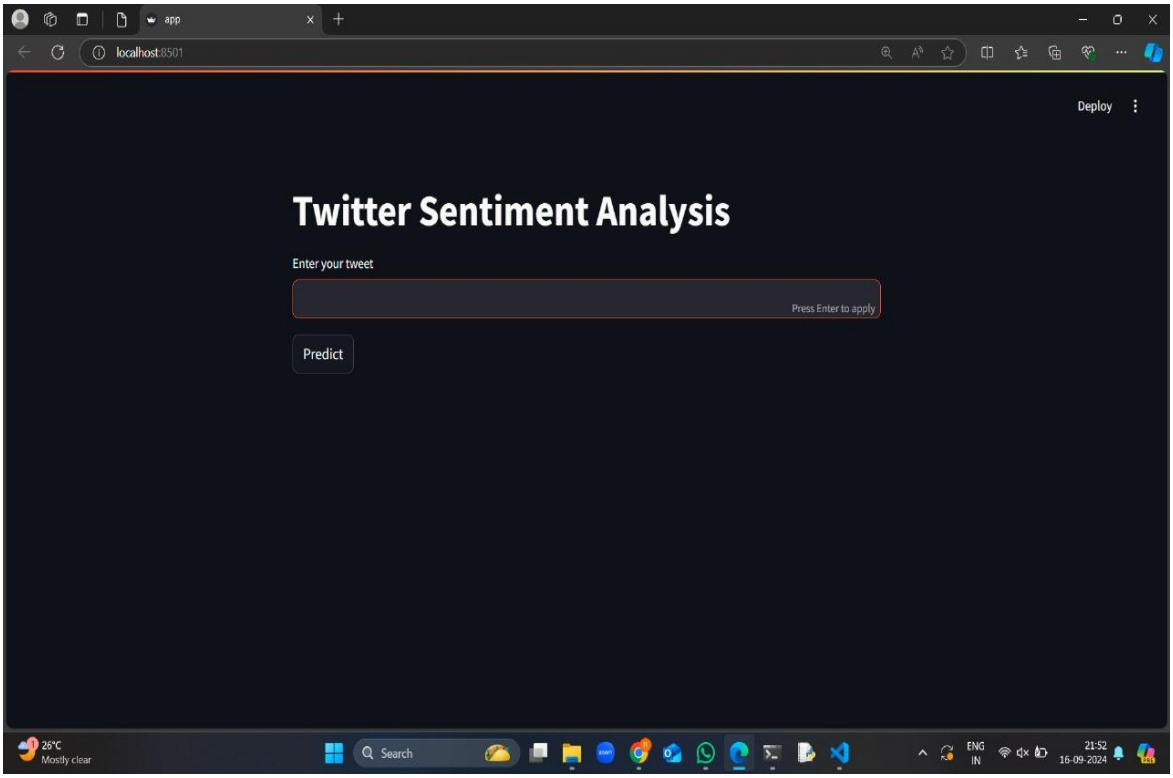


Fig 8.1

The image showcases a Twitter Sentiment Analysis application with a simple and intuitive user interface. It runs on a local server, as indicated by the localhost:8501 address in the browser's address bar. The interface has a dark theme and features a text input box where users can type in a tweet. Below this, a "Predict" button initiates the sentiment analysis process.

The input field is currently empty, and a placeholder text, "Please Enter to apply," is visible, suggesting the user must press "Enter" after typing a tweet. The top-right corner displays a "Deploy" menu, hinting at possible deployment options or settings. The application's clean and functional design is geared toward testing or development purposes. The desktop environment in the background further indicates that the application might still be in a testing phase or locally hosted for initial evaluations. It represents a straightforward sentiment analysis tool.

Negative Interface:

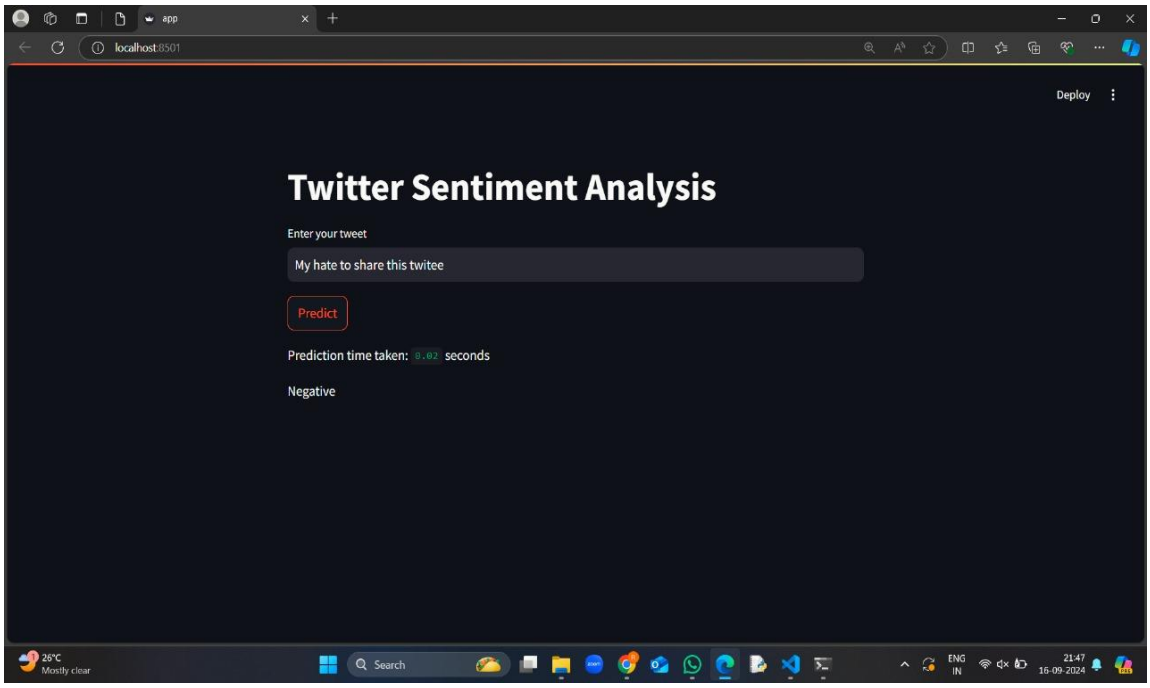


Fig 8.2

The image displays a web-based application for Twitter Sentiment Analysis. The interface is minimalistic, with a text input box where users can type or paste a tweet. Below the input field, there is a "Predict" button that triggers the sentiment analysis process. The sample tweet entered in the box reads, "My hate to share this tweet." Once the prediction is performed, the app displays the sentiment as "Negative," with the prediction time noted as 0.02 seconds, emphasizing the tool's efficiency.

The page uses a dark theme, making it visually appealing and easier on the eyes. The design is straightforward, catering to ease of use for end-users. At the top-right corner, a menu button labelled "Deploy" suggests additional functionalities or deployment options might be available. The image also includes a glimpse of a desktop environment, showcasing the application running on localhost. This appears to be a project likely under testing or development.

Positive Interface:

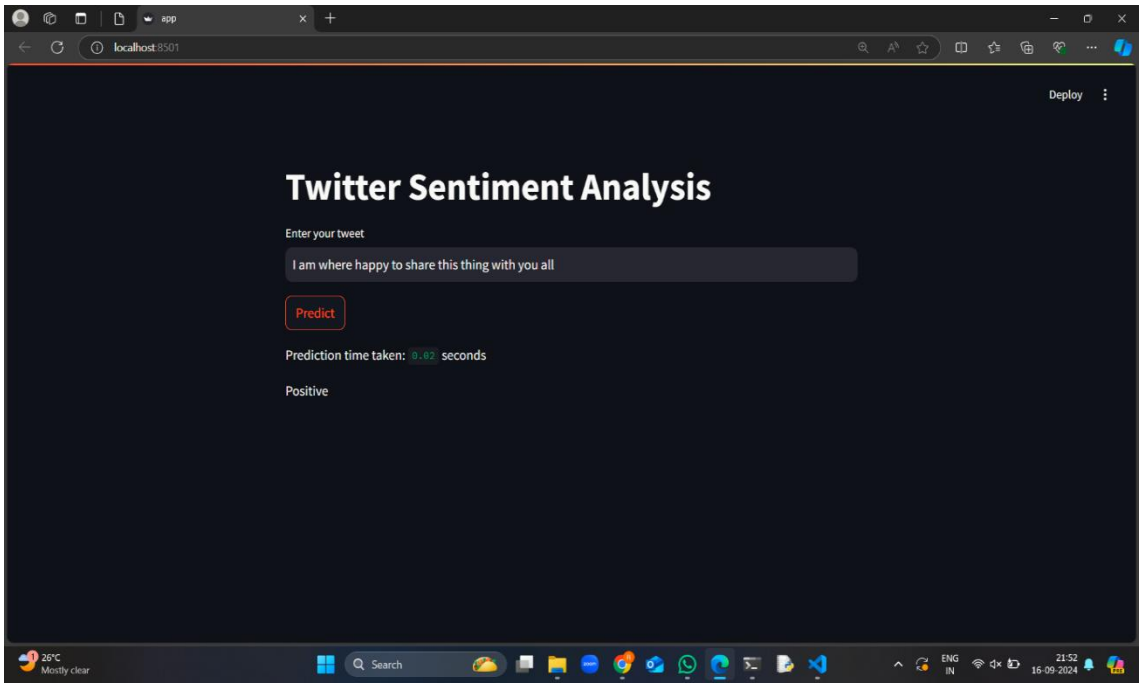


Fig 8.3

This image represents the output screen of a Twitter Sentiment Analysis web application with a positive sentiment prediction. The interface features a dark theme and a simple, user-friendly layout. At the top, the title "Twitter Sentiment Analysis" is displayed prominently. Below it, there is an input field labeled "Enter your tweet," where users can type their text. For a positive output, the input could be a statement like, “i am where happy to share this thing with you all!” Once the user clicks the “Predict” button, the application quickly processes the text and displays the result. The prediction output would indicate "Positive," along with a short prediction time, such as 0.02 seconds.

This clear and efficient interface demonstrates the functionality of the application, providing accurate and fast sentiment predictions. It is ideal for analyzing public opinions or emotions on social media posts in real time.

Neutral Interface:

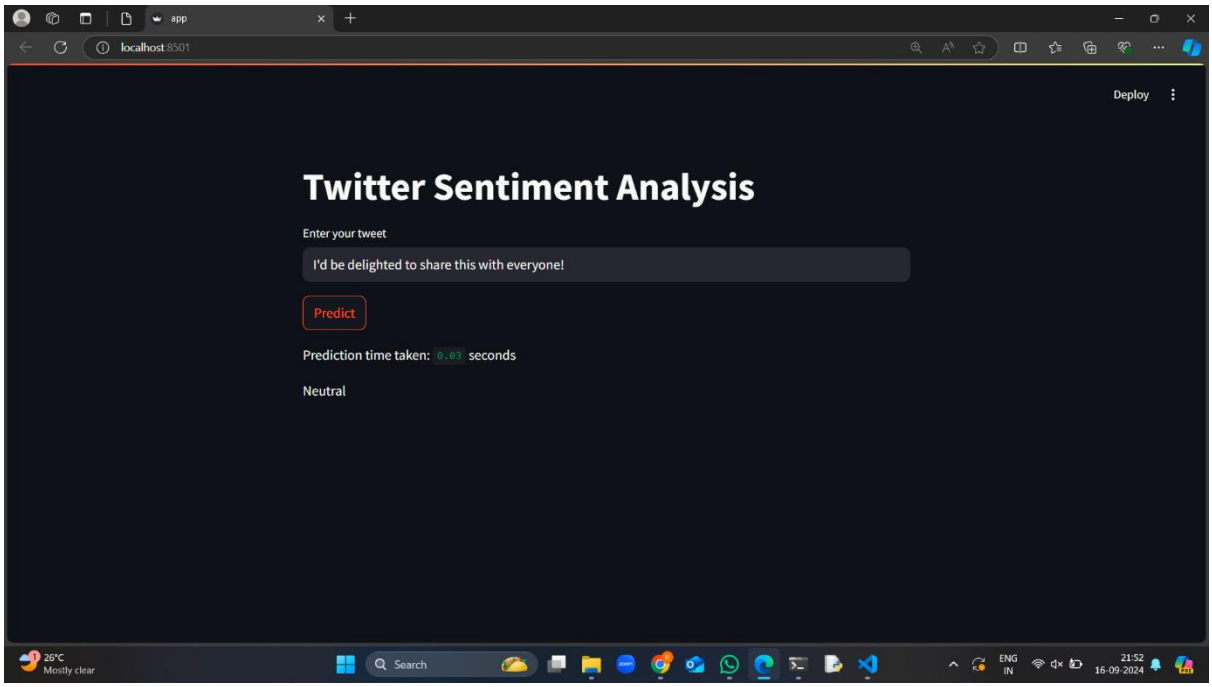


Fig 8.4

This image shows the output screen of a Twitter Sentiment Analysis web application, featuring a neutral sentiment prediction. The interface maintains a clean, dark-themed design with a straightforward structure. At the top, the title "Twitter Sentiment Analysis" is prominently displayed. Below it, an input field labelled "Enter your tweet" allows users to type their text.

For a neutral output, the input might be a statement like, “I’d be delightable to share this with everyone.” After the user clicks the “Predict” button, the application processes the text within seconds and displays the result. In this case, the prediction would read "Neutral," along with the processing time, such as 0.02 seconds.

This tool offers a user-friendly way to analyze tweets and determine whether the sentiment is positive, negative, or neutral. It provides valuable insights into public opinion or general attitudes, useful for businesses, researchers, and social media enthusiasts.

9. CONCLUSION

In conclusion, Twitter sentiment analysis is a powerful tool that provides valuable insights into public opinion, emotions, and reactions on a wide range of topics. As one of the most active social media platforms, Twitter serves as a rich source of real-time data, with millions of tweets posted every day. These tweets often reflect raw, immediate sentiments about breaking news, product launches, political events, or social issues. By applying sentiment analysis techniques, businesses, governments, and organizations can gain a better understanding of public attitudes, enabling them to make informed decisions and improve engagement strategies. The key strength of Twitter sentiment analysis lies in its ability to process large volumes of unstructured data quickly, providing a snapshot of collective opinion in near real-time. For example, brands can use sentiment analysis to monitor consumer feedback, track brand perception, and detect potential PR crises. Similarly, politicians and policymakers can use sentiment data to gauge voter opinions on various issues and tailor their messaging accordingly. The entertainment industry, too, benefits from understanding audience reactions to new releases, events, or celebrity actions. Despite its strengths, Twitter sentiment analysis faces several challenges.

The informal, abbreviated, and sometimes sarcastic language used in tweets makes it difficult for algorithms to accurately interpret sentiment. For instance, words with multiple meanings, contextual nuances, or irony can lead to misclassification. Moreover, the presence of slang, emojis, and hashtags further complicates the analysis, as they may not always follow conventional language rules. While machine learning models have made significant advancements in handling these issues, ensuring accuracy in sentiment classification remains a complex task.

10. FUTURE ENHANCEMENT

The future of Twitter sentiment analysis holds exciting possibilities, fuelled by advancements in artificial intelligence (AI), natural language processing (NLP), and machine learning (ML). One key enhancement is **improved contextual understanding** through advanced NLP models, such as BERT, GPT, and T5. These transformer-based models can better capture complex language nuances, including sarcasm, irony, and cultural context, which are often challenging for current sentiment analysis systems.

Another important area of improvement is **multilingual and cross-cultural sentiment analysis**. As Twitter users span different countries and languages, the ability to analyze tweets in multiple languages with regional slang and idioms will become increasingly vital. Enhanced models could help brands and organizations understand global sentiment, offering insights that are more inclusive of diverse linguistic and cultural expressions.

11. REFERENCES

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