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FAKE NEWS DETECTION USING MACHINE LEARNIING

Sanskar Yadav[1], Riya Dwivedi[2], Nitin Yadav[3], Mrs Sonia S B[4]

[1,2,3]UG Student, Department of Information Science and Engineering, Atria Institute of Technology, Bangalore, Karnataka, India.

[4]Professor, Department of Information Science and Engineering, Atria Institute of Technology, Bangalore, Karnataka, India.

Abstract: Analysis of public information from social media could yield interesting results and insights into the globe of public opinions about almost any product, service or personality. Social network data is one amongst the foremost effective and accurate indicators of public sentiment. The explosion of Web 2.0 has led to increased activity in Podcasting, Blogging, Tagging, Contributing to RSS, Social Bookmarking, and Social Networking. As a result there has been an eruption of interest in people to mine these vast resources of knowledge for opinions. Sentiment Analysis or Opinion Mining is that the computational treatment of opinions, sentiments and subjectivity of text. during this paper we are going to be discussing a strategy which allows utilization and interpretation of twitter data to see public opinions. Developing a program for sentiment analysis is an approach to be accustomed computationally measure customers' perceptions. This paper reports on the look of a sentiment analysis, extracting and training an unlimited amount of datasets. Results classify customers' perspective via datasets into positive and negative, which is represented during a chart, bar diagram, scatter plot using php, css and html pages.

Keywords: data processing, linguistic communication processing, Naïve Bayes.

INTRODUCTION

Sentiment is an attitude, thought, or judgment prompted by feeling. Sentiment analysis, which is additionally called opinion mining, studies people's sentiments towards certain entities. Internet could be a resourceful place with reference to sentiment information. From a user's perspective, people are able to post their own content through various social media, like forums, micro-blogs, or online social networking sites. From a researcher's perspective, many social media sites release their application programming interfaces (APIs), prompting data collection and analysis by researchers and developers. for example, Twitter currently has three different versions of APIs available [6], namely the remainder API, the Search API, and therefore the Streaming API. With the remainder API, developers are able to gather status data and user information; the Search API allows developers to question specific Twitter content, whereas the Streaming API is able to collect Twitter content in real time. Moreover, developers can mix those APIs to create their own applications. Hence, sentiment analysis seems having a powerful fundament with the support of massive online data.

However, those sorts of online data have several flaws that potentially hinder the method of sentiment analysis. the primary flaw is that since people can freely post their own content, the standard of their opinions can not be guaranteed. for instance, rather than sharing topic-related opinions, online spammers post spam on forums. Some spam are meaningless at all, while others have irrelevant opinions also referred to as fake opinions . The second flaw is that ground truth of such online data isn't always available. A ground truth is more sort of a tag of a particular opinio n, indicating whether the opinion is positive, negative, or neutral. The Stanford Sentiment 140 Dataset Corpus is one of the datasets that has ground truth and is additionally public available. The corpus contains 1.6 million machine- tagged Twitter messages.

Microblogging websites have evolved to become a source of various quite information. this can be thanks to nature of micro blogs on which individuals post real time messages about their opinions on a spread of topics, discuss current issues, complain, and express positive sentiment for products they use in standard of living. In fact, companies manufacturing such products have began to poll these microblogs to urge a way of general sentiment for his or her product. Many time these companies study user reactions and reply to users on microblogs. One challenge is to build technology to detect and summarize an overall sentiment.

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Our project Tweezer resembles the analyze of datasets by the peoples on certain products of companies or brands or performed by political leaders. so as to try to this we analyzed datasets from Twitter. Datasets are a reliable source of info. mainly because people dataset about anything and everything they do including buying new products and reviewing them. Besides, all datasets contain hash tags which make identifying relevant datasets a straightforward task. variety of research works has already been done on twitter data. Most of which mainly demonstrates how useful this information is to predict various outcomes. Our current research deals with outcome prediction and explores localized outcomes.

We collected data using the Twitter public API which allows developers to extract datasets from twitter programmatically. The collected data, due to the random and casual nature of dataset, have to be filtered to get rid of unnecessary information. Filtering out these and other problematic datasets like redundant ones, and ones with no proper sentences was done next.
As the preprocessing phase was tired certain extent it was possible to ensure that analyzing these filtered datasets will give reliable results. Twitter does not provide the gender as a question parameter so it is insufferable to obtain the gender of a user from his or her datasets. It clothed that twitter doesn't kindle user gender while opening an account in order that information is seemingly unavailable.

LITERATURE SURVEY

Paper I: Detecting Fake News Spreaders in Social Networks using Inductive Representation Learning
An important aspect of preventing fake news dis semination is to proactively detect the likelihood of its spreading .Research in the domain of fake news spreader detection has not been explored much from a network analysis perspective. In this paper, we propose a graph neural network based approach to identify nodes that are likely to become spreaders of false information. Using the community health assessment model and interpersonal trust we propose an inductive representation learning framework to predict nodes of densely-connected community structures that are most likely to spread fake news, thus making the entire community vulnerable to the infection. Using topology and interaction based trust properties of nodes in real-world Twitter networks, we are able to predict false information spreaders with an accuracy of over 90% .

Paper II: Fake News Early Detection: An Interdisciplinary Study
Massive dissemination of fake news and its potential to erode democracy has increased the demand for accurate fake news detection. Recent advancements in this area have proposed novel techniques that aim to detect fake news by exploring how it propagates on social networks. Nevertheless, to detect fake news at an early stage, i.e., when it is published on a news outlet but not yet spread on social media, one cannot rely on news propagation information as it does not exist. Hence, there is a strong need to develop approaches that can detect fake news by focusing on news content. In this paper, a theory-driven model is proposed for fake news detection.

Paper III: Fake news detection: a survey of evaluation datasets
Fake news detection has gained increasing importance among the research community due to the widespread diffusion of fake news through media platforms. Many dataset have been released in the last few years, aiming to assess the performance of fake news detection methods. In this survey, we systematically review twenty-seven popular datasets for fake news detection by providing insights into the characteristics of each dataset and comparative analysis among them. A fake news detection datasets characterization composed of eleven characteristics extracted from the surveyed datasets is provided, along with a set of requirements for comparing and building new datasets. Due to the ongoing interest in this research topic, the results of the analysis are valuable to many researchers to guide the selection or definition of suitable datasets for evaluating their fake news detection methods.

Paper IV: Fake news detection based on subjective opinions.
Fake news fluctuates social media, leading to harmful con sequences. Several types of information could be utilized to detect fake news, such as news content features and news propagation features. In this study, we focus on the user spreading news behaviors on social me dia platforms and aim to detect fake news more effectively with more accurate data reliability assessment. We introduce Subjective Opinions into reliability evaluation and proposed two new methods. Experiments on two popular real-world datasets, BuzzFeed and PolitiFact, validates that our proposed Subjective Opinions based method can detect fake news more accurately than all existing methods, and another proposed probability based method achieves state-of-art performance.

Paper V: Language-based User Representations for Fake News Detection
Cognitive and social traits of individuals are reflected in language use. Moreover, individuals who are prone to spread fake news online often share common traits. Building on these ideas, we introduce a model that creates representations

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of individuals on social media based only on the language they produce, and use them to detect fake news. We show that language-based user representations are beneficial for this task. We also present an extended analysis of the language of fake news spreaders, showing that its main features are mostly domain independent and consistent across two English datasets. Finally, we exploit the relation between language use and connections in the social graph to assess the presence of the Echo Chamber effect in our data.

PROPOSED SYSTEM

The basic components of the full program are often expressed as follows.The important elements are :
• Data Set Loading: -The building blocks of our project are Data sets and machine learning algorithms .
• Data Pre-Processing - this system is employed to get rid of stop words ,drop duplicate and take away meaningless char from text.
• Feature Selection: Feature Selection is that the method of reducing the input variable to your model by using only relevant data and getting eliminate noise in data. it's the method of automatically choosing relevant features for your machine learning model supported the kind of problem you're trying to unravel.
• Applying Classification and Model Construction: classification may be a supervised learning concept which basically categorizes a group of information into classes. the foremost common classification problems are – speech recognition, face detection, handwriting recognition,
• Classifying the new data: during this step we test the classification model by providing unlabled data and check how the classification model is functioning for brand spanking new data .

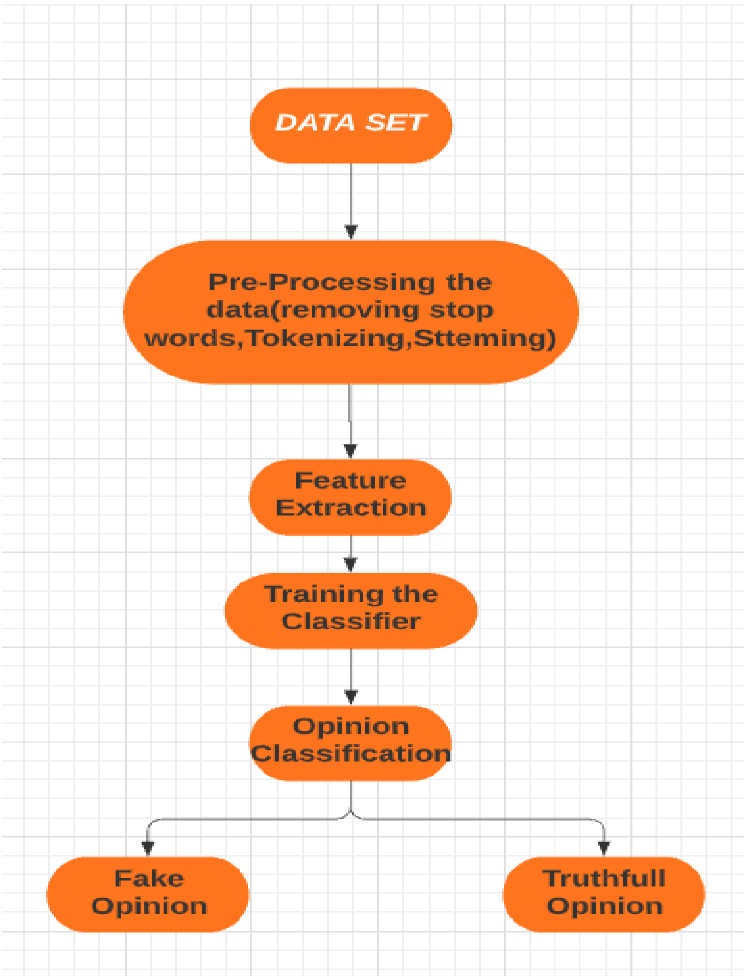

Figure 4.1 : The System Activity Diagram

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FLOW CHART

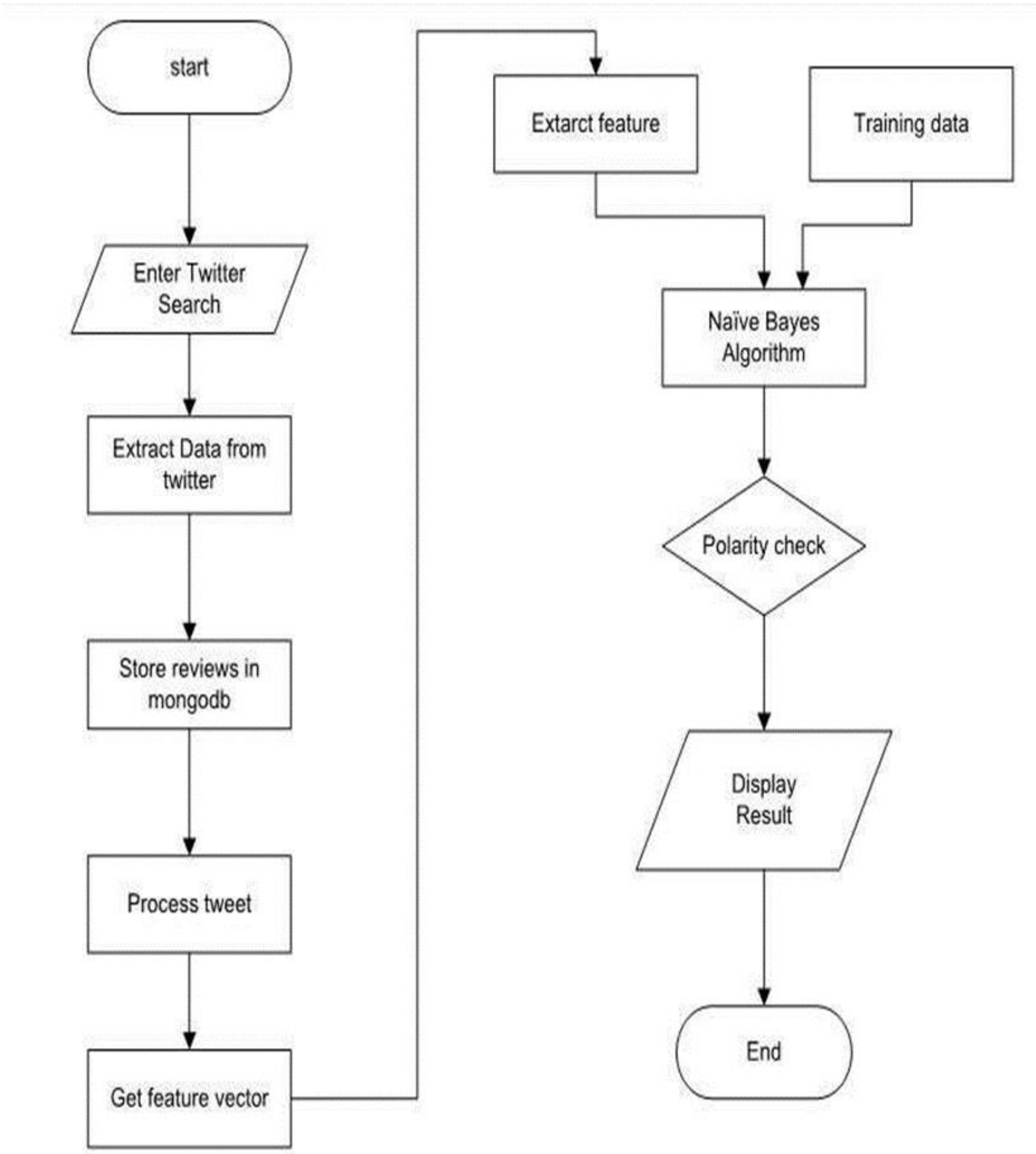

Figure 4.1 : The System Flowchart

The above diagram elaborates the flow of the processes we plan to use for the execution of our project. The Encoder takes in the input text and creates v embeddings which have the characteristics of the unique text. The Synthesizer generates a grapheme or phoneme sequence from the input text using Machine learning algorithms. The outputs of the encoder and synthesizer generates a Mel-Spectrogram that is used by the algorithms to provide the final output in the most aspirated voice without the need to train the system again.

IMPLEMENTATION

- **Implementation**

The system-wide implementation includes processes such as installing prerequisites, configuring the environment for the project to function properly, retrieving datasets, encoding and implementing encoder modules, synthesizer modules, and vocoder modules. As mentioned above, all coding and required implementation was done in Python 3

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V.II Installations

The mandatory installations that are required for the working of the project included

- click==7.1.2
- Flask==1.1.2
- gunicorn==20.0.4
- itsdangerous==1.1.0
- Jinja2==2.11.2
- joblib==0.17.0
- MarkupSafe==1.1.1
- nltk==3.5
- numpy==1.19.2
- pickle-mixin==1.0.2
- regex==2020.10.23
- scikit-learn==0.23.2
- scipy==1.5.3
- sklearn==0.0
- threadpoolctl==2.1.0
- tqdm==4.51.0
- Werkzeug==1.0.1
- xgboost==1.1.1

The above installation was done using the Python pip in Python shell. Once the installation is complete, you would like to configure the new installation to form the acceptable environment for our work and accessing our project work. this is often done using the demo_cli.py file. If the demo_cli.py file runs successfully, the wants are successfully installed and configured.

- **MongoDB**

MongoDB is an open source database that uses a document-oriented data model. MongoDB is one in every of several database types to arise within the mid-2000s under the NoSQL banner. rather than using tables and rows as in relational databases, MongoDB is made on an architecture of collections and documents. Documents comprise sets of key-value pairs and are the essential unit of information in MongoDB. Collections contain sets of documents and performance because the equivalent of relationa l database tables.

- **Python**

Python may be a widely used high-level, general-purpose, interpreted, dynamic programming language. Its design philosophy emphasizes code readability, and its syntax allows programmers to precise concepts in fewer lines of code than possible in languages like C or Java. The language provides constructs intended to enable writing clear programs on both a little and huge scale.

- **Implementation of Feature generation**

All document is represented as a feature vector over the space of dictionary words. for every document, keep track of dictionary words together with their number of occurrence therein document. Formula used for algorithms:

$$\phi_{k|label=y} = P(x_j = k \mid label = y)$$

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$\phi_{k|label=y}$ = probability that a particular word in document of label(neg/pos) = y will be the k^{th} word in the dictionary.

m = Number of words in i^{th} document.

n_i = Total Number of documents.

- **NLTK**

NLTK may be a leading platform for building Python programs to figure with human language data. It provides easy-to-use interfaces to over 50 corpora and lexica l resources like WordNet, together with a collection of text processing libraries for classification, tokenization, stemming, tagging, parsing, and semantic reasoning, wrappers for industrial-strength NLP libraries, and a full of life discussion forum.

NLTK has been cal ed “a wonderful tool for teaching, and working in, linguistics using Python,” and “an amazing library to play with tongue.” NLTK is suitable for linguists, engineers, students, educators, researchers, and industry users alike. Natural Language Processing with Python provides a practical introduction to programming for language processing. Written by the creators of NLTK, it guides the reader through the basics of writing Python programs, working with corpora, categorizing text, analyzing linguistic structure, and more.

- **PHP**

PHP is an HTML-embedded, server-side scripting language designed for web development. it's also used as a general purpose programming language. PHP codes are simply mixed with HTML codes and might be utilized in combination with various web frameworks. Its scripts are executed on the server. PHP code is processed by a PHP interpreter. the most goal of PHP is to permit web developer to form dynamically generated pages quickly. A PHP file consists of texts, HTML tags and scripts.

TESTING AND DEBUGGING

- **Unit Testing**

Unit testing is performed for testing modules against detailed design. Inputs to the process are usually compiled modules from the coding process. Each modules are assembled into a bigger unit during the unit testing process. Testing has been performed on each phase of project design and coding. we supply out the testing of module interface to make sure the proper flow of knowledge into and out of the program unit while testing. We confirm that the temporarily stored data maintains its integrity throughout the algorithm's execution by examining the loc al organisation. Finally, all error-handling paths are tested.

- **System Testing**

We usually perform system testing to seek out errors resulting from unanticipated interaction between the sub-system and system components. Software must be tested to detect and rectify all possible errors once the ASCII text file is generated before delivering it to the shoppers. for locating errors, series of test cases must be developed which ultimately uncover all the possibly existing errors. Diffe rent software techniques may be used for this process. These techniques provide systematic guidance for designing test that

- Exercise the inner logic of the software components
- Exercise the input and output domains of a program to uncover errors in program function, behaviour and performance.

We test the software using two methods: White Box testing: Internal program logic is exercised using this action at law design techniques. recorder testing: Software requirements are exercised using this action at law design techniques.

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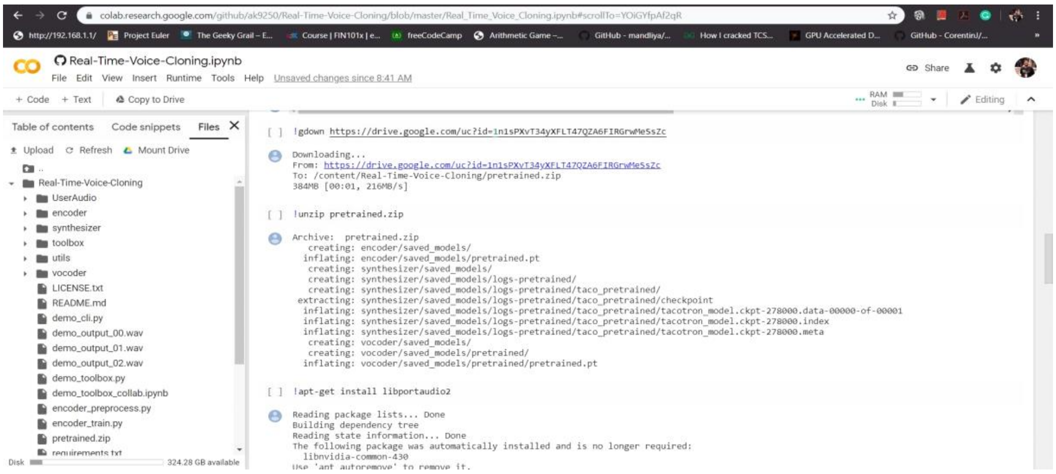

Figure 6.1 : Uploading the project for testing on Google Collab

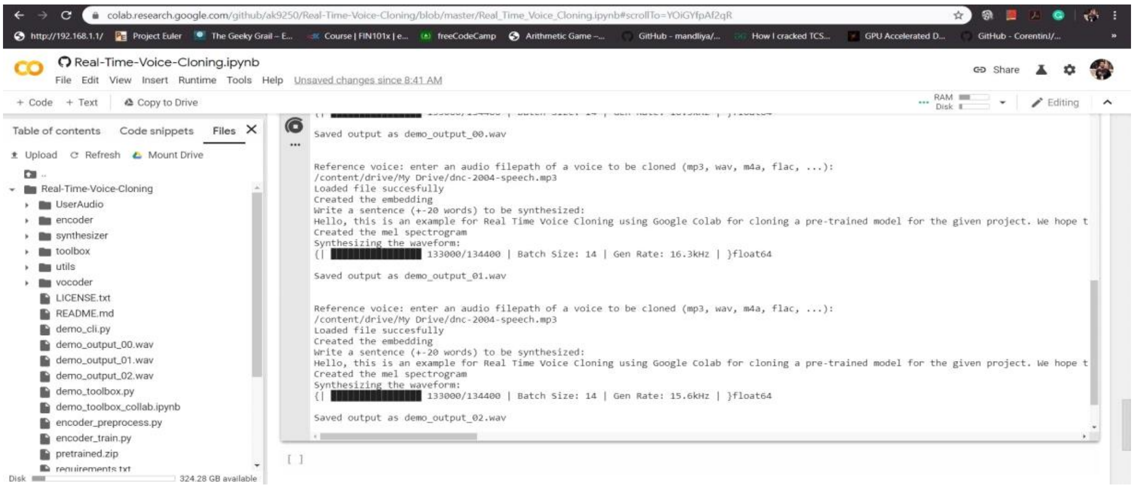

Figure 6.2 : The output obtained on Google Collab while testing.

This signified successful testing of initial project

DEBUGGING

The main issues encountered during implementation and testing were environment and installation issues. Therefore, it was helpful to reinstall modules such as PyTorch and Webrtcvad with lower version specifications and customizations. Another bug we encountered was the toolbox used to open an instance before closing it immediately. Proper investigation revealed that this was happening because the root directory was not passed to the record path. After passing the required root directory command, I found that the system was working properly. The other errors I encountered were trivial and could be fixed by checking the code.

RESULT

We collected dataset containing positive and negative data. Those dataset were trained data and was classified using Naïve Bayes Classifier. Before training the classifier unnecessary words, punctuations, meaning less words were cleaned to get pure data. To determine positivity and negativity of datasets we collected data using twitter API. Those data were stored in database and then retrieved back to remove those unnecessary word and punctuations for pure data. To check polarity of test dataset we train the classifier with the help of trained data. Those results were stored in database and then retrieved back using php, html , javascript and css.

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After facing a number of errors, successful elimination of those error we have completed our project with continuous effort. At the end of the project the results can be summarized as:

- A user friendly web based application.
- No expertise is required for using the application.
- Organizations can use the application to visualize product or brand review graphically.

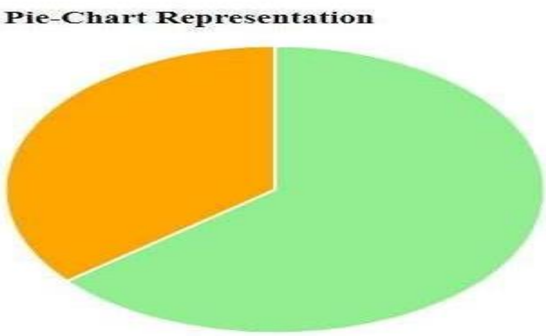

Fig :"Pie-Chart Representation"

Fig: The front end viewed by the user .

CONCLUSION

We have completed our project using python as language, Php with Html and python for output presentation. Although there was a controversy in integration of python and php, through numbers of instructional we were ready to integrate it. We were ready to determine the positivity and negativity of every dataset. Based on those datasets we represented them in a very diagrams like bar chart, Pie-chart and scatter plot. All the diagrams associated with outcome are shown in fig . a little conclusion is additionally shown during output presentation supported product or brand entered. Our designed system is user friendly.
All displaying results are displayed in webpage.

FUTURE SCOPE

- Analyzing sentiments on emo/smiley.
- Determining neutrality.
- Potential improvement can be made to our data collection and analysis method.
- Future research can be done with possible improvement such as more refined data and more accurate algorithm.

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