Social Media Listening for Public Response Analysis on Twitter

ABSTRACT

Microblogging today has become a very popular communication tool among Internet users. Millions of users share opinions on different aspects of life everyday. Therefore microblogging websites are rich sources of data for opinion mining and sentiment analysis. Sentiment analysis deals with identifying and classifying opinions or sentiments expressed in the source text. Social media is generating a vast amount of sentiment-rich data in the form of tweets, status updates, blog posts etc. Twitter sentiment analysis technology provides methods to survey public emotion about the events or products related to them.

The purpose of this project is to build an algorithm that can accurately classify Twitter responses as positive or negative, with respect to a trending term. This paper reports on the design of a sentiment analysis, extracting a vast amount of tweets. Our hypothesis is that we can obtain high accuracy on classifying sentiment in Twitter responses using machine learning techniques. Generally, this type of sentiment analysis is useful for concerned political authorities, sports persons, corporate industries and other influential personalities, etc. We represented the different categories of results such as pie charts, wordclouds, temporal charts and geographical heatmaps in order to analyze the responses effectively.

We developed a web application with an intuitive user interface using React and Django which displays the live-trends, and the Django server fetches the trending topics from twitter periodically which classifies and analyzes the same by extracting the tweets using the twitter API. We have also showcased that the analysis can be done from 2 perspectives, that is, profile-centric and trend-centric. In profile-centric, we have picked up a particular post and performed our analysis on its replies while in trend-centric we have picked various tweets related to a certain trend.

1. INTRODUCTION

Social media platforms have become an important site for political conversations throughout the world. It is becoming a key medium through which we communicate with each other [1]. Microblogging sites like Twitter, Facebook, Instagram, etc, have millions of people sharing their thoughts daily because of their characteristic short and simple manner of expression. Political leaders, governments, and states operate within this social media environment, wherein they continually address crises and institute damage control through platforms such as Twitter. In general, the following profiles often tend to have massive follower support on social media portals:

- Concerned political authorities
- Corporate giants
- Sports person & athletes
- Other Influential personalities, like social activists, actors, etc.

Twitter Social Media has become a central site where people express their opinions and views on political parties and candidates. Twitter data tends to be utilized more than those from other social media platforms. This is in part because of Twitter's more liberal data availability [2]. Emerging events or news are often followed almost instantly by a burst in Twitter volume, providing a unique opportunity to gauge the relation between expressed public sentiment and electoral events. This further refines social listening, which refers to sentiment analysis of the public responses and navigating through social conversation for achieving more popularity and better interaction with the general public. Sentiment analysis attempts to determine the disposition of a speaker, essayist, or other subjects in terms of theme via extreme emotional or passionate responses to an archive, communication, or occasion [3]. It helps to explore how these events affect public opinion. It provides answers to the most important issues by making automated decisions based on a significant amount of data rather than plain intuition that isn't always right. It offers the public, the media, politicians, and scholars a new and timely perspective on the dynamics of the electoral process and public opinion. Our project aims to pick up a few of the controversial topics and analyze how the people have responded to them. This would allow the concerned authorities to judge the results of their action and take the necessary steps accordingly.

Significant Research Highlights

- Emotional inclination of people on Twitter social media
- Word clouds of frequently used words in positive & negative context
- Count of positive & negative tweets in a day-wise & time-wise manner
- Geographic analysis of tweeted posts in positive & negative context

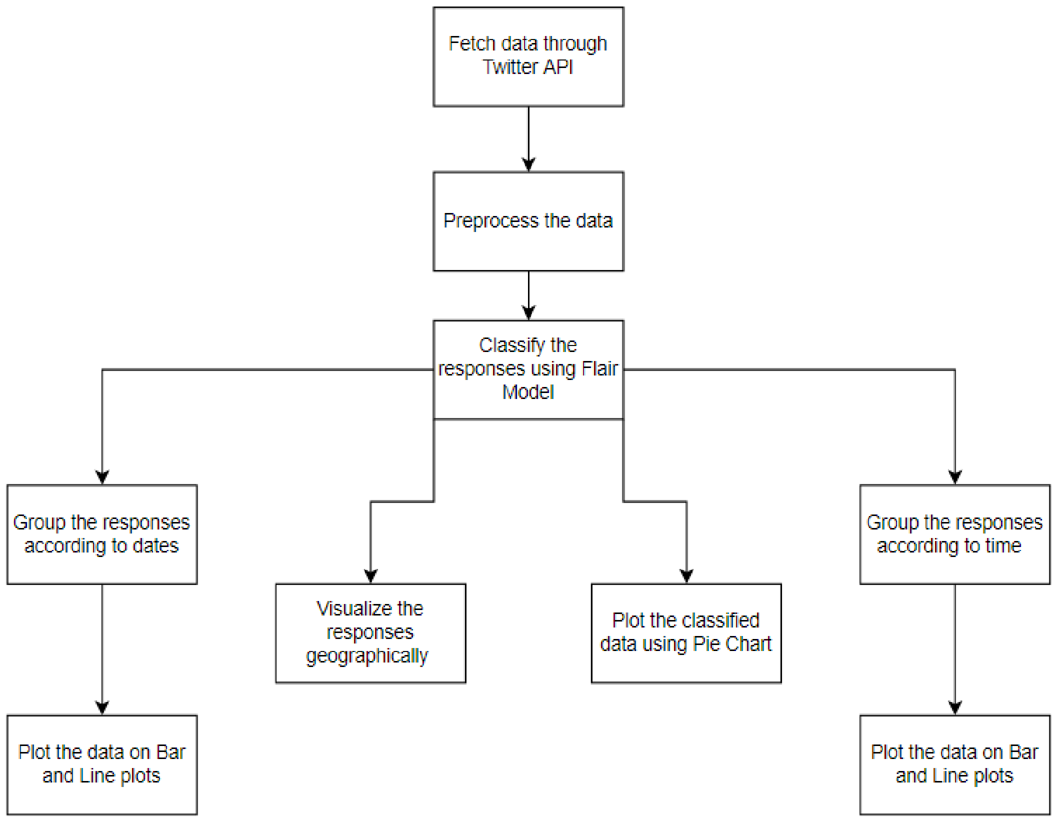


Figure 1. Program Flow Diagram of Proposed Research

Figure 1 shows the flow of the main algorithm we used in our project. As a first step, we created a Twitter Developers account and fetched the real time data using the twitter API. The data is then processed using regex and translated to English using the google-trans library. After selecting an accurate working library, we used the 'en-sentiment' classifier provided by the Flair library to classify the preprocessed data. After that, we grouped the data using different parameters such as date, time, geographical location and quantitative distribution and plot them using appropriate graphs.

2. RELATED WORK

There have been many papers written on sentiment analysis for the domain of blogs and product reviews. In paper [4], the authors provided a survey and comparative study of existing techniques for opinion mining including machine learning and lexicon-based approaches, together with cross domain and cross-lingual methods and some evaluation metrics. Yet in another paper [5], the authors describe a system for analysis of public sentiment towards their company or product, as expressed on Twitter.

Also, instead of presenting the sentiment polarity of each tweet relevant to the topic, some have focussed their study on hashtag-level sentiment classification [6]. This task aims to automatically generate the overall sentiment polarity for a given hashtag in a certain time period, which markedly differs from the conventional sentence-level and document-level sentiment analysis.

Another research conducted in [7], attempts to analyze Twitter posts about electronic products like mobiles, laptops, etc using the Machine Learning approach. With sentiment analysis being done in a specific domain, it is possible to identify the effect of domain information in sentiment classification. The authors presented a new feature vector for classifying the tweets as positive, negative and extracting opinions about products. Similarly, attempts to analyze customers' perspectives toward the critical to success in the marketplace have been made [8].

In [9], the authors implemented the Naive Bayes algorithm using the sentiment140 training dataset to improve the classification. The use of SentiWordNet along with Naive Bayes improved the accuracy of classification of tweets, by providing positivity, negativity, and objectivity score of words present in tweets. The authors in paper [10], “Semantic Video Classification Based on Subtitles and Domain Terminologies” proposed an algorithm which is based on the WordNet lexical database and the WordNet domain and applies Natural Language Processing techniques on subtitles.

In paper [11], authors are combining NLP and Deep learning approaches to build a model which predicts genres of movies such as drama, romance, horror and action and also analyze their popularity based on live tweets data on Twitter social networking website. In yet another research, a lexicon-based approach has been adopted to perform entity-level sentiment analysis followed by using additional tweets that are likely to be opinionated and identified automatically by exploiting the information in the result of the lexicon-based method [12]. Another work [13] involved the development of a convolution algorithm on Twitter sentiment analysis to train deep neural networks, in order to improve the accuracy and analysis speed. First, they learned global vectors for word representation by unsupervised learning on a large Twitter corpora, which expresses the word sentiment information as the word embeddings. Afterwards, we concatenate these word representations with the prior polarity score feature and state of-the-art features as a sentiment feature set.

The authors in [14], authors performed a linguistic analysis of their corpus and showed how to build a sentiment classifier that uses the collected corpus as training data. Moreover, in paper [15], authors examined the effectiveness of applying machine learning techniques to the sentiment classification problem. A challenging aspect of this problem that seems to distinguish it from traditional topic-based classification was that while topics are often identifiable by keywords alone, sentiment can be expressed in a more subtle manner. So, apart from presenting their results obtained via machine learning techniques, they also analyzed the problem to gain a better understanding of the difficult level. Motivated from the existing research, we have performed a spatial and temporal analysis of social media trends and examined the public sentiment associated.

3. PROJECT UTILITY

Our project will provide assistance to people and organizations having influential profiles so as to track the public views and sentiments on their social media posts in form of tweets, decisions, and products. It can help the government officials to track the responses of people from states that supported or opposed official policies, laws and decisions made by authoritarian bodies. Such influential personalities may belong to any of the following organizations:

- Small-scale or Private Corporate Sectors
- Public Commercial Firms
- Political Bodies
- Social Circles

4. TOOLS & TECHNOLOGIES

Our research initiative was implemented using Python which is considered as modular with fast execution and extensive support for different libraries. The following section shows the libraries and Application Programming Interfaces (APIs) used for our experimentation.

4.1. Language

- Python
- Javascript

4.2. Libraries

- tweepy: An easy-to-use Python library for accessing Twitter API.
- googletrans: A library to translate text
- pandas: Library to work easily and efficiently with large dataframes
- numpy: Library to perform mathematical operations on large datasets
- flair: Main NLP library for the sentiment analysis
- textblob: simple API for diving into common NLP
- vader: rule-based sentiment analysis library
- WordCloud: A library to visualize the words according to their frequency
- matplotlib: A library for creating visualizations
- geopandas: A library to plot the geographical data

4.3. API

- Twitter API: An API to fetch data from Twitter
- Mapbox: API used for Geolocation

4.4. Frameworks

- Django Rest Framework: Toolkit for building powerful Web APIs.
- React: Frontend framework for building user interfaces

5. IMPLEMENTATION

We began our project with the data collection by creating a twitter developer's account and then fetched the real-time data with various attributes, namely, username, description, verified user, location, following, followers, total_tweets, retweet_count, listed_count, created, tweet_id, favourite_count, favourited, retweeted, language, text, is_quote_status, quote_status_id, quote_count, hashtags. After that we cleaned up the data and selected an appropriate library by performing a comprehensive comparison. Then finally, we classified the data using the selected library and analyzed it by plotting.

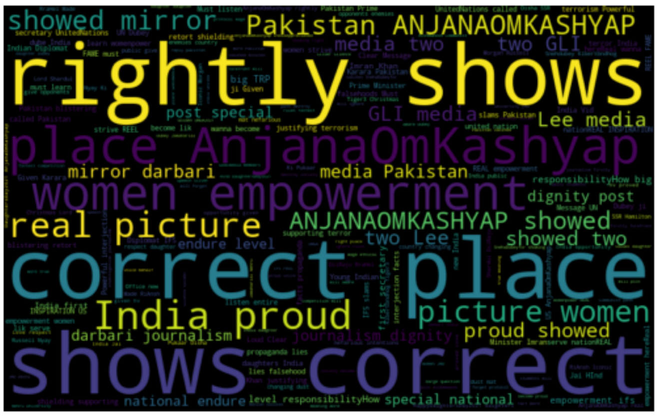
i. Fetch data: Created a Twitter developer account to get the authentication keys and then with the help of the tweepy library, we fetched the required tweets.

ii. Preprocessing: We used Regex to clean up the responses and then translated all the tweets to English using googletrans library.

iii. Library Selection: We tried classifying our dataset and did a comprehensive comparison between the following libraries:

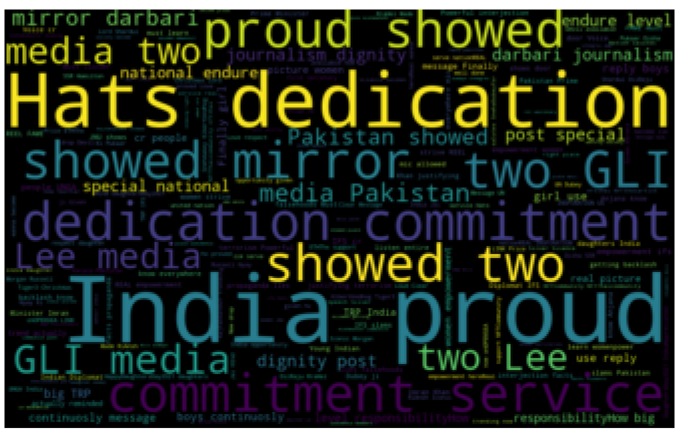
- TextBlob
- Vader
- Flair

Positive Wordclouds



TextBlob

Vader

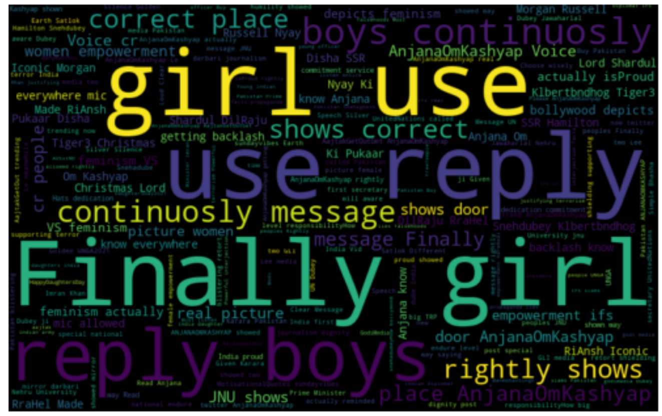


Flair

Figure 2. Positive WordClouds

Neutral

TextBlob



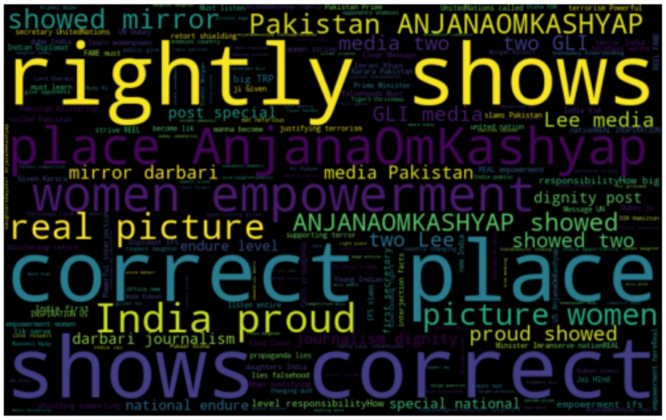
Vader

Flair

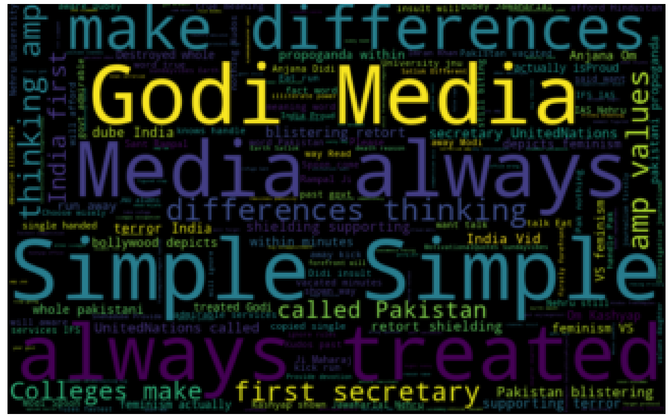
Figure 3. Neutral WordClouds

Figure 2 and 3 are showing the positive and neutral wordclouds respectively, as obtained from the three libraries, namely TextBlob, Vader and Flair. The comparative analysis of all three positive wordclouds as well as the three neutral wordclouds shows that all the libraries generated almost similar results for positive and neutral tweets.

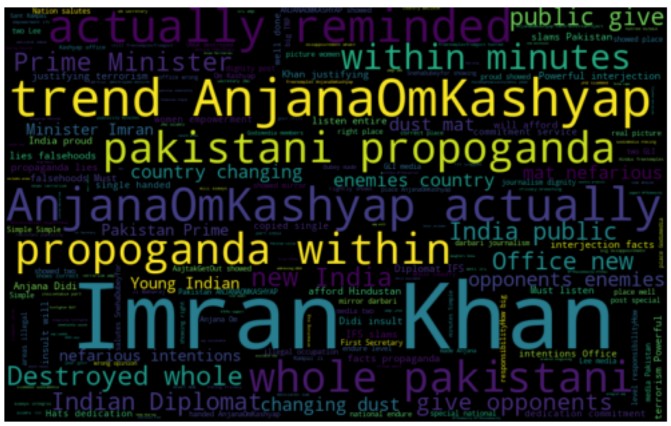
Negative



TextBlob



Vader



Flair

Figure 4. Negative WordClouds

Figure 4 shows the negative wordclouds generated from three above stated libraries. It is very much evident from the wordclouds that the negative tweets are best represented by Flair.

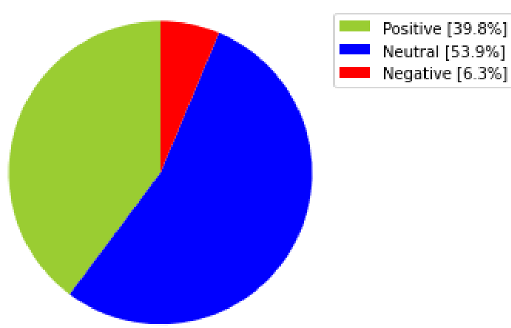


Figure 5. Percentage distribution as classified by TextBlob

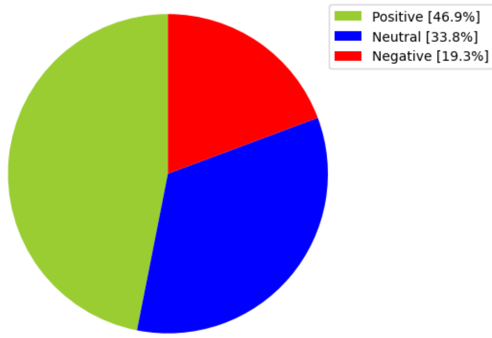


Figure 6. Percentage distribution as classified by Vader

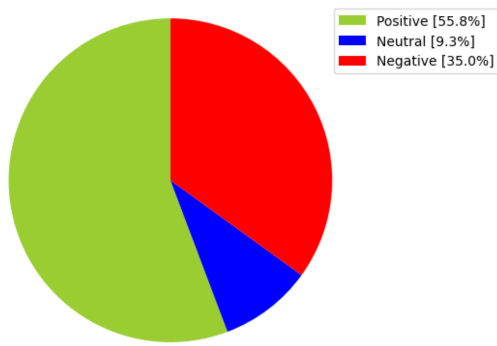


Figure 7. Percentage distribution as classified by Flair

Figure 5, 6 and 7 are showing the percentages of positive, neutral and negative tweets we got from the used three models. We can see that the maximum percentage of positive tweets is obtained from Flair model which was required, based on the trend #sneha_dubey. After interpreting all the above wordclouds and pie charts, we came to the conclusion that the Flair model provides the most accurate results for our use case. Hence, we decided to proceed with Flair for the rest of the application.

iv. Classification: We classified the responses into 5 major categories, that are very positive, positive, neutral, very negative, and negative. We did it by using the Flair model. It classifies the text into two labels, either positive or negative, and gives its confidence score on the respective scales out of 100.

For our experimentation, we have considered the following threshold standards:

- if the label is positive:
    - score >= 0.85, then it's very positive
    - 0.70 <= score < 0.85, then it's positive
    - score < 0.70, then it's neutral

- if the label is negative:
  - score >= 0.85, then it’s very negative
  - 0.70 <= score < 0.85, then it’s negative
  - score < 0.70, then it’s neutral

v. Assembling: We assembled the responses into two groups using the attribute ‘created at’. For that, we used a dictionary with key as date and value as the frequency of responses on that date to group according to date and similarly another dictionary has the time of response as key and value as the frequency of responses at that time to group according to time.

vi. Visualization: We analyzed the responses using the following plots:

- Pie Chart: Created a pie chart showing the percentages of people who are in support and against the chosen topic.
- Line & Bar Plot: Analyzed the responses according to the tweet date and time.
- Geographical Heat Maps: Visualized the positive and negative responses according to the geographical distribution.

vii. Dashboard Design & Working: To set up the backend for our dashboard, we created a Django server using the django-rest-framework and deployed it using Heroku. The server is responsible for periodically fetching the trending topics from twitter and generating the above graphs. The list of paths for these graphs are then served on a separate endpoint, for the frontend to consume.

For the frontend, we decided to go with React, as it is fast and easy to set up, along with material UI for the visual appeal. This is responsible to fetch the necessary data, like, the list of the live trends, list of paths of plots etc, from the backend and present it to the user on an intuitive UI. The frontend has been deployed using Netlify.

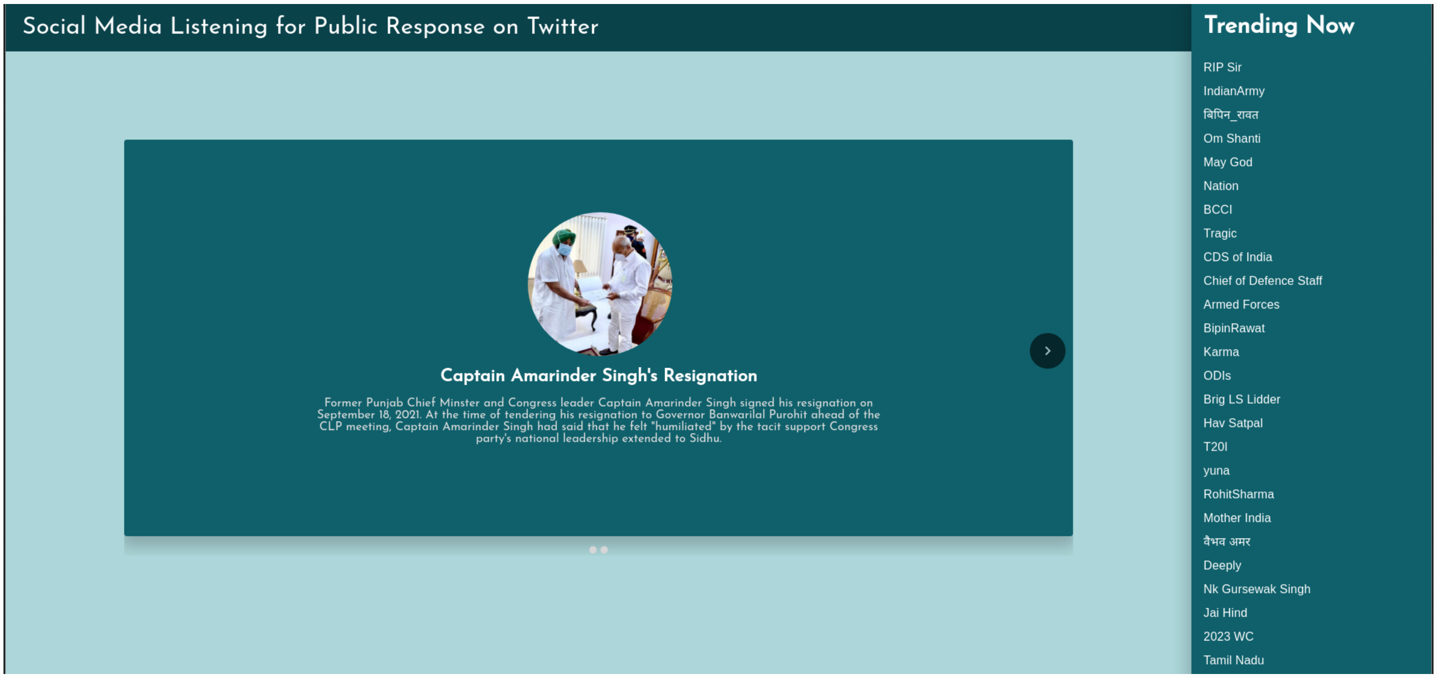


Figure 17. Homepage of the website=

We displayed trend centric (#Sneha_Dubey) and profile centric (tweet by Captain Amarinder Singh) responses on the homepage and at the right column, there are all live trends which get updated periodically.

6. RESULTS & ANALYSIS

We have conducted our experimentation and analysis on a sensitive social media trend, *#SnehaDubey*, which received a massive public response. Sneha Dubey, the IFS officer (2012 batch) who gave a fiery response to Imran Khan at the UN. While India often ignores Pakistan's statements at the world body, Indian diplomat Sneha Dubey exercised the right to respond to Imran Khan. She accused Pakistan of giving shelter to the 9/11 mastermind Osama bin Laden who was killed by US special forces in a 2011 raid in the army city of Abbottabad.

6.1 Word-cloud Formation

- Frequently used words relative to tweets having a very positive context

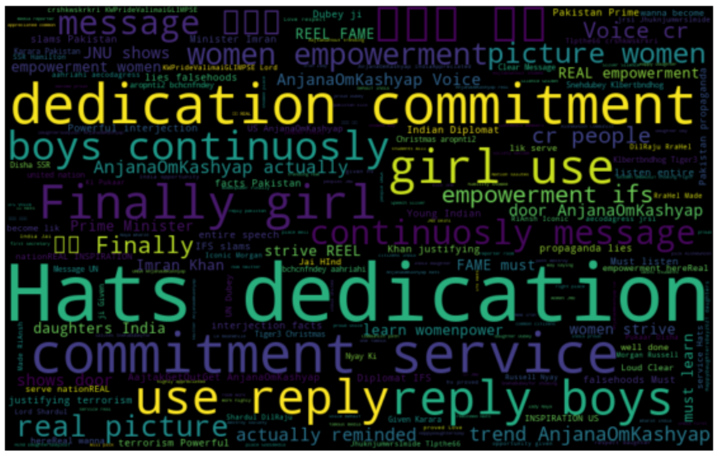


Figure 8. Word Cloud for Very positive results

- Frequently used words relative to tweets having a positive context

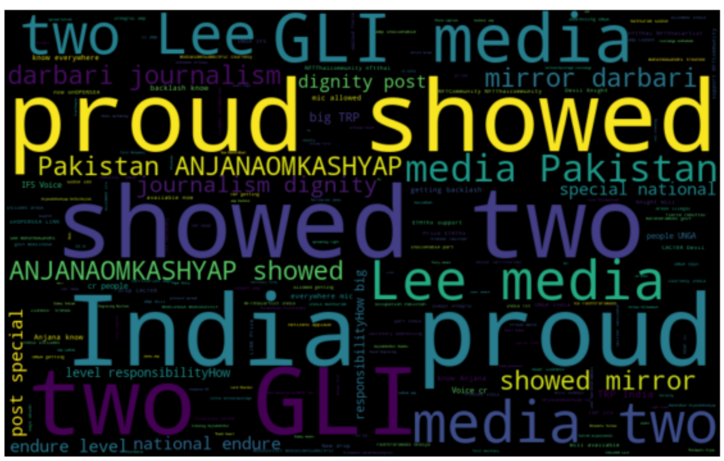


Figure 9. Word Cloud for Positive Results

6.2 Emotional Behavioral Analysis

Figure 10 shows the sentiment analysis for the trend #Sneha_Dubey which is classified into 5 different categories. We can see that around 55% of the people were in support of the speech delivered by Sneha Dubey at the UN, thus reflecting the nation's positive acknowledgement of her official statement.

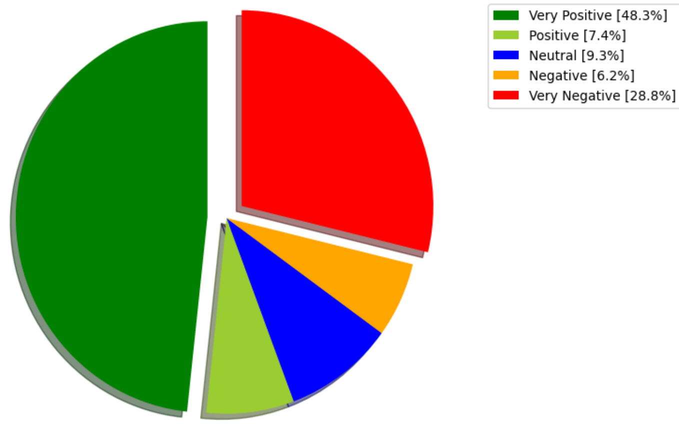


Figure 10. Sentiment Analysis Result for #SnehaDubey

6.3 Temporal Analysis

Figure 11 and 12 show that this topic received the maximum number of responses, both positive and negative, in the first two days. After that, the frequency of responses descended as the days passed. So we can infer that as the trend gets older, the responses of the people to a particular trend decreases.

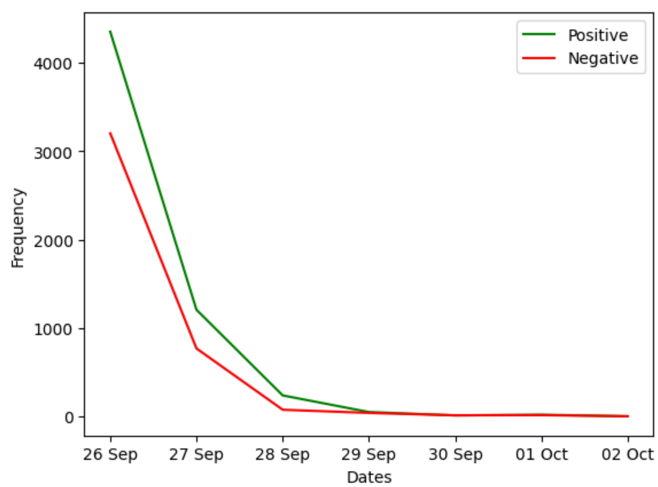


Figure 11. Line plot showing the trend of responses in a day-wise manner

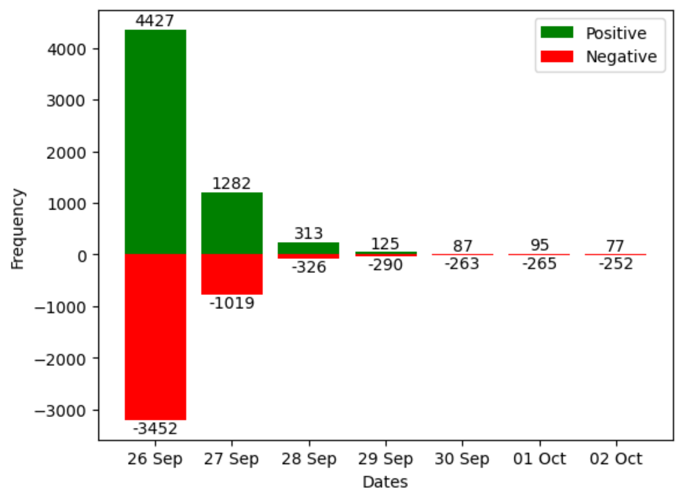


Figure 12. Bar plot showing the frequency of responses in a day-wise manner

Figure 13 and 14 show that the rate of positive responses is at the peak at 7 am, 10 am, and 1 pm. Whereas, the rate of negative responses is at the peak at around 12 pm. They also show that the people were most active on Twitter from 8 am to 4 pm.

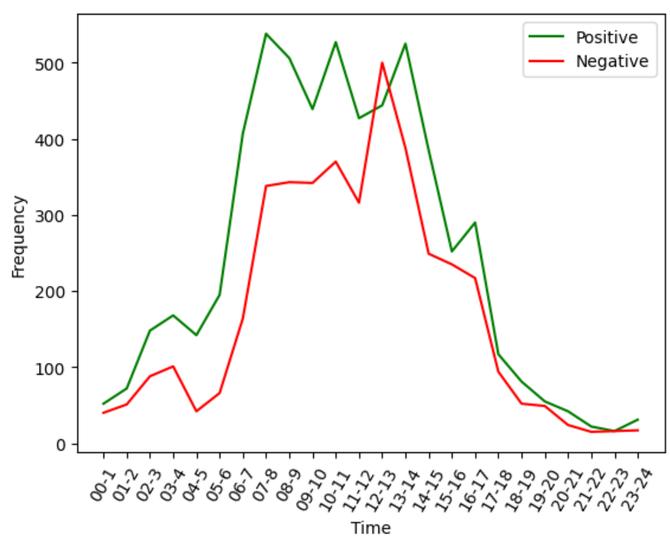


Figure 13. Line plot showing the trend of responses in a time-wise manner

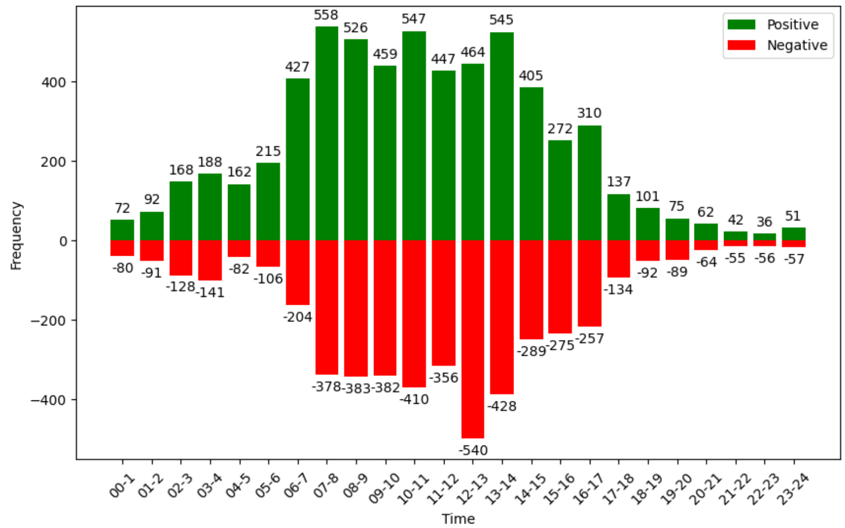


Figure 14. Bar plot showing the frequency of responses a time-wise manner

6.4 Geographical Analysis

A graphical analysis is conducted to examine the demography of the public response to the social media trend. According to Figure 15 and 16, the geographical distribution of both positive and negative responses is similar. The graphs show a high percentage of positive and negative responses from Uttar Pradesh and Maharashtra, while the other states had comparatively lesser participation to the trend

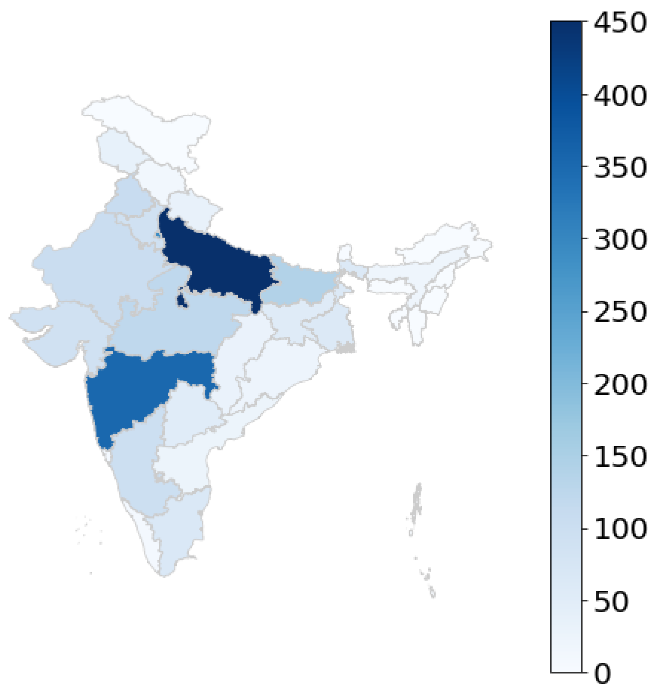


Figure 15. Geographical Heat Map of Positive Responses

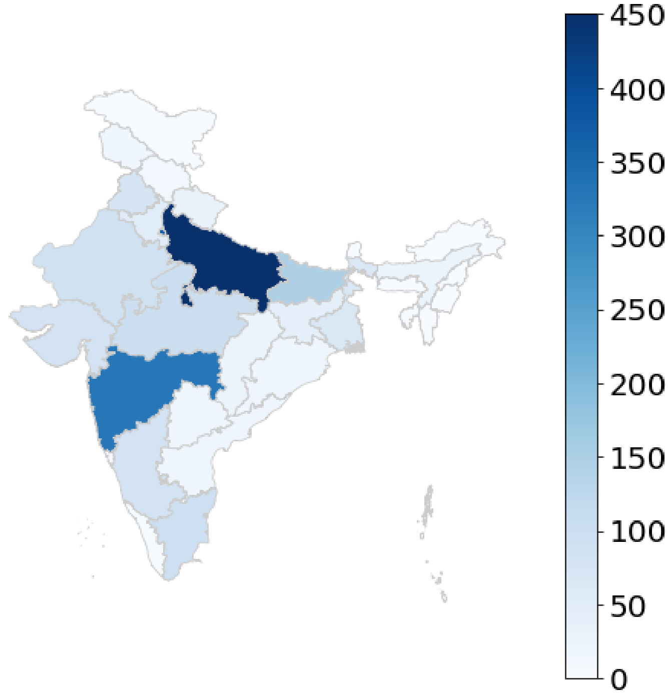


Figure 16. Geographical Heat Map of Negative Responses

A graphical analysis is conducted to examine the demography of the public response to the social media trend. According to Fig 6.8 and Fig 6.9, the geographical distribution of both positive and negative responses is similar. The graphs show a high percentage of positive and negative responses from Uttar Pradesh and Maharashtra, while the other states had comparatively lesser participation in the trend.

7. CONCLUSION

Social listening refers to analyzing the public responses and navigating through social conversation for achieving more popularity & better interaction with the general public. Sentiment analysis provides answers to the most important issues by making automated decisions based on a significant amount of data rather than plain intuition that isn't always right. Our aim of performing sentiment analysis using the 'en-sentiment' classifier provided by the Flair library on specific trends/profile was successful as our application is correctly able to classify the tweets and visualize the different categories of results such as

- Pie chart to get a clear idea of the percentage of people supporting or opposing the trend
- Wordclouds to get a qualitative perspective
- Temporal charts to analyze the activity of the users
- Geographical heatmaps to get the geographical distribution of the responses

On the basis of public responses, concerned authorities will get huge benefits as they would be able to determine the impact of their decisions and the area they should work more.

8. FUTURE PLAN

- There is scope for setting an interactive and more customized public responses dashboard for profile-centric Twitter posts. For instance, the user can search for any handle and the latest tweets will be displayed on the dashboard and then the user can see the analysis of those tweets.
- We can also potentially increase the flexibility of our website by adding a feature which allows the user to search for any trend and see it's analysis.

9. REFERENCES

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