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Twitter based sentimental analysis of Covid-19 observations

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ABSTRACT

The emergence of social media has provided people with the opportunity to express their feelings and thoughts about everything and everything in their lives. There is a massive amount of textual stuff available, and approaches are required to make meaningful use of the information provided by isolating and evaluating the different types of text. Sentimental Analysis is a method of obtaining a human being's point of view through mining his or her emotions. The entire world is sharing their thoughts on social media on the Corona Pandemic that is now underway. This research presents an analysis of attitudes in order to determine whether or not people are optimistic in the face of a difficult circumstance. The technique of polarity is employed by the paper in order to determine if an opinion is positive, negative, or nonpartisan [1]. In order to determine the polarity, the following three major keywords are used: "COVID", "Corona virus," and "COVID-19."

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1. Introduction

Corona virus caused an uncontrollable pandemic catastrophe that spread around the world. It is an illness that has a significant impact on the respiratory health of human beings. It was originally identified in Wuhan, China, in December of this year, and it has since spread throughout the world. The World Health Organization labeled it a pandemic in March 2020. Because to the widespread nature of the outbreak, practically all countries have implemented lockdown [2]. No one is allowed to leave their homes or interact with other people during a lockdown situation. During the months of March to May, practically the entire world was under house arrest and working from home. Some research has found that lockdown has a psychological influence on human behavior, such as anxiety, despair, and frustration, among other things. All of these actions have a negative impact on a human being's health [3]. Their social media comments mirror how they use the platform in general. As a result, we may determine positive, negative, or neutral human behavior [1] by looking at social comments. Because of the aforementioned, this study uses emotional analysis of Twitter comments to determine how people feel about the Covid-19 vaccine. Understanding one's own point of view on the subject is a time-consuming process due to the enormous amount of posts on social media.

With the help of text analytics, Sentimental Analysis is a method of analysing emotions, that analyses and categorises different emotions. As a result, sentiment analysis is being used in this work. This research presents textual analysis of Twitter information to understand public perceptions of fear, which is directly associated to widespread Coronavirus sickness [4]. We also discuss how textual analytics can be used to track the advancement of fear in the media. The remainder of the paper is organised as follows: The second section is devoted to the review of the literature. Section 3 discusses the methodology that was used for the project. Section 4 contains the results and analysis of Twitter comments, followed by a conclusion in Section 5. Section 5 concludes the discussion.

2. Literature review

People's extensive use of social media to voice their thoughts on a wide range of topics generates a large amount of information on the internet. Analysis and analysis are continuously

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dealing with this issue, attempting to figure out how to translate the vast amount of information available on the internet into valuable knowledge. Sentiment Analysis is one of the fields that allows the analyzers to keep track of how people are feeling about a given keyword [5]. A number of researchers are engaged in this endeavor. Aliza and colleagues described the construction of a sentiment mining system based on the extraction of a large number of tweets. They divided client feedback received through tweets into categories such as positive and negative [1] and categorized them further. Hamid and Johari demonstrated the use of sentiment recognition to gather information from Twitter. Their research looked into the impact of sentiment mining on numerous themes ranging from politics to humanity and came to the conclusion that sentiment mining had a significant impact [6]. Jim and colleagues discovered user sentiment related to the epidemic by analyzing Coronavirus-specific tweets. They came to the conclusion that they had gained insights into the progression of fear-sentiment through

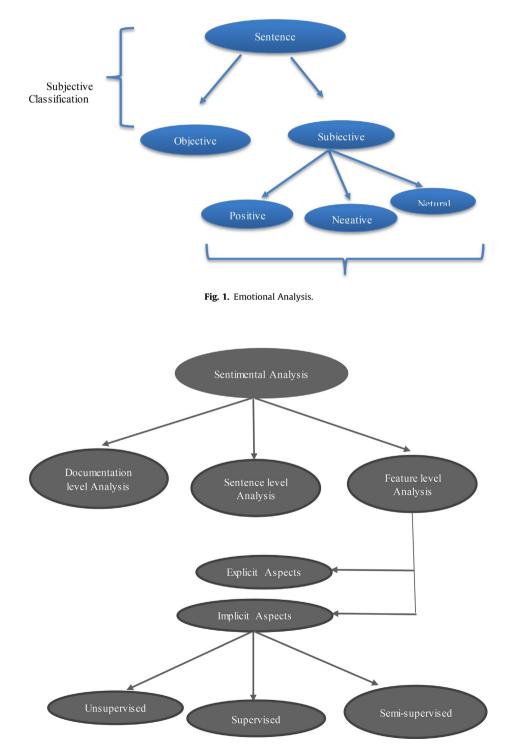


Fig. 2. Sentimental Analysis at Various Granularity Levels.

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time when the coronavirus neared high levels in the United States of America [4]. Seniti Circles, a dictionary-based technique for sentiment recognition in social media content such as Twitter tweets, was developed by Hassan et al. The technique took into account At both the entity and tweet levels, they are aware of what they personally thought [7] [7a]. In contrast to the traditional sentence-level and report-level emotions studies, Xiao long et al. proposed the hashtag-level sentimental mining technique, which generates a broad emotional analysis for a single hashtag across a specific time period. [8]. When it comes to forecasting, Rameshwer et al. discussed the importance of notion inquiry [9]. As of right now, every human being on the face of the planet is operating under the COVID-19 pandemic condition. As a result, assessing people's perceptions of the situation is beneficial for maintaining a pleasant environment [10]. For COVID-19 treatment, four distinct deep CNN architectures are investigated on pictures of chest X-rays. As a result, with this in mind, we are doing sentiment recognition for the purpose of identifying the same. The model is trained and tested using a collection of data sets of covid 19 X-ray imageries and non-covid 19 X-ray imageries [21].

2.1. Sentimental analysis

The most important thing to remember while undertaking sentimental analysis is to detect whether a statement is subjective or objective in nature. There are no further substantial activities required if the supplied line is assigned as a goal, however if the given line is delegated as subjective, it is necessary to determine its polarity (i.e., whether it is positive, negative, or nonpartisan) [11]. As demonstrated in Fig. 1, emotional analysis separates a sentence into two types of separations: subjectivity and polarity separations.

As illustrated in Fig. 2, client-generated content on the Internet can be inspected at three astonishing granularity levels: documentation level, sentence level, and feature level [12], with the documentation level being the most detailed.

Document Level: This level is used to categorise the entire document into good, negative, and neutral categories, among others. [12].

Sentence Level: It separates the document into sentences and assigns a positive, negative, or neutral label to each one.

Feature Level: It just uses one feature and displays the results in respect to the feature chosen. "The iPhone is fantastic, but they still need to improve battery life and security issues," for example, considers three points: "iPhone" (positive), "battery life" (negative), and "security.".

2.2. Emoji's and how to handle them

In each tweet, the number of good and negative emoji's used is counted, and the following standards are applied [14]: The term "positive" will 'be used to describe a tweet that contains at least one positive emoji and no negative emoji's. The term "negative" will be used to describe a tweet that contains at least one negative emoji and no good emoji's. The tweet is regarded as obscure if none of the other principles described above can be applied to it [14].

3. Methodology

Fig. 3 displays the steps in the planned project. This section walks you through the first three steps one by one.

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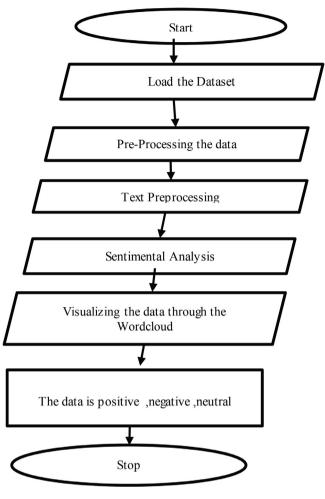


Fig. 3. Proposed Flow Work.

3.1. Proposed FrameWork

We provide a platform with several levels for sentiment analysis (see Fig. 4). The initialization layer is responsible for data collection and message preprocessing. Positive, negative, and neurotic layers comprise the evaluation layer.

3.2. Creating Twitter accounts and exploiting Twitter tweets

When accessing information from the Twitter website, it is necessary to verify its legitimacy. As a result, the first step is to configure your Twitter credentials in order to view the Twitter comments. The Sentimental Analysis is mostly concerned with textual data, which necessitates a greater amount of text processing [15]. We gathered data on testing for three search terms: "COVID," "Coronavirus," and "Covid-19" as part of this research. This trio of terms is frequently and mostly utilized by people on social media platforms. As a result, the search phrase used in this work contained all of these keywords.

3.3. Data set preparation and preparation

Pre-processing, also known as data cleaning, is required before to doing categorization on any data collection. Pre-processing is the process of cleaning data. Pre-processing is the act of removing A. Vijayaraj, K. Bhavana, S. SreeDurga et al.

material or content from a document that is not necessary for sentimental analysis, such as punctuation, photos, hyperlinks [16,15], and other such items [16,15]. Fig. 4 shows an example of a snippet for cleaning up the information.

Proposed Algorithm for Sentimental Analysis:

char.sentiment(text): blob = TextBlob(text)sentiment_polarity = blob.sentiment.polarity; sentiment_subjectivity = blob.sentiment.subjectivity; if (sentiment_polarity > 0) sentiment_label = 'Positive'; elseif (sentiment_polarity < 0) sentiment_label = 'Negative'; else sentiment_label = 'Neutral'; result = { 'polarity':sentiment_polarity, 'subjectivity':sentiment_subjectivity, 'sentiment':sentiment_label; ł return result;

4. Observation and analysis of results

This section of the study presents the results or three keywords: "COVID," "CORONAVIRUS," and "COVID-19," as well as

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emotive analysis on Twitter comments [1,6,7]. It also includes a discussion of the implications of these findings. A Sentimental Analysis of the Keyword "COVID" is presented in Section A. We created a Word Cloud to represent the number of times the word "COVID" appeared in a Twitter dataset, as shown in Fig. 4. As a result, we can see the frequency of the keyword "COVID" [4,17] by looking at the Word Cloud. Following that, we calculated the relationship between subjectivity and polarity for the same and displayed it with a scatter plot in Fig. 5. When it comes to presenting the values for Cartesian coordinates are utilized for two constants in the data set [18]. In this case, subjectivity determines whether a word is subjective or

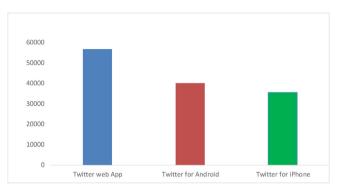


Fig. 5. Top three on Sources of dataset.

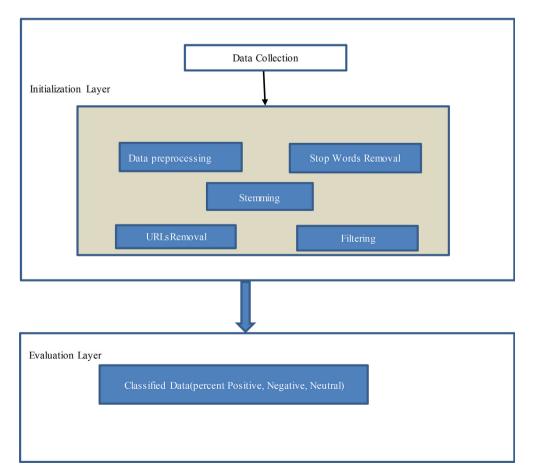


Fig. 4. Proposed Frame Work.

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objective. Polarity, on the other hand, teaches us about a person's positive and negative responses to a given keyword or phrase. The zero point is represented by the point "zero" in the polarity column [18,19]. As a result, everything to the left of zero denotes negative feedback, whereas everything to the right of zero denotes positive feedback. The percentage of neural tweets is larger than the percentage of positive and negative tweets in the emotional analysis for all three terms, which is not surprising. Even in these circumstances, People are maintaining positive as well as neutral attitudes in the face of chaotic illness spread scenarios [2,3], as evidenced by the larger percentage of positive tweets compared to negative tweets.

Fig. 5 show the sources on the dataset. The top three according on the datasets are Twitter web app, Twitter for Android, Twitter for iPhone. The Twitter Web App score is 56,891 and the Twitter for Android score is 40179, the twitter for iPhone is 35472. These are the top three sources on the dataset.

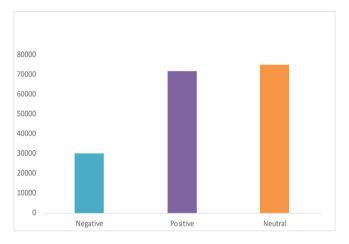


Fig. 6. Sentimental Analysis.

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Different Applications	Counts
Twitter web App	56,891
Twitter for Android	40,179
Twitter for iphone	35,472

Fig. 6 shows on the Sentimental Analysis. The comments on Negative, Positive, Neutral. The X-axis is the sentiment and Y-axis is the count. The Negative score is 29918. The Positive score is 74590.The Neutral score is 77546, by using module sentimental Analysis.

Comments	Counts
Negative	30,000
Positive	72,000
Neutral	75,000

Fig. 7 Sentimental Analysis for Positive words and the x-axis are words and y-axis are counts. The cases are 10780, new are 98954, amp are 55493, positive are 4892 and soon by the according to Diagram.

Fig. 8 Sentimental Analysis for Negative words and the x-axis are words and y-axis are counts. The cases are 2580, amp are 1970, positive are 1805, the pandemic are 897 and soon by the according to Diagram.

Fig. 9 shows the word cloud for positive words. The positive words are in the word cloud are amp, pandemic, day, cases, help, confirmed, case, people, read, going, government and soon

Fig. 10 shows the wordcloud for negative words. The positive words are in the wordcloud are amp, COVID19, time, people, active case, cases sooner, slow spread, help slow, risk cases, new, day, today and soon.

Fig. 11 shows the word cloud for neutral words. The neutral words are in the word cloud are amp, today, need, pandemic, cases death, mask, trump, patient, test, know, help and soon.

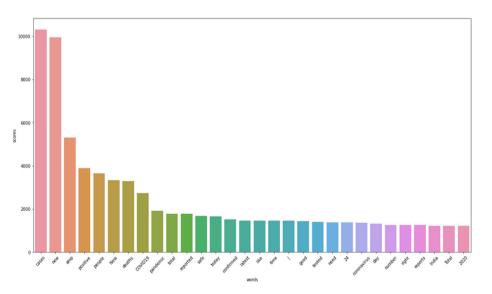


Fig. 7. Sentiment Analysis for Positive Words.

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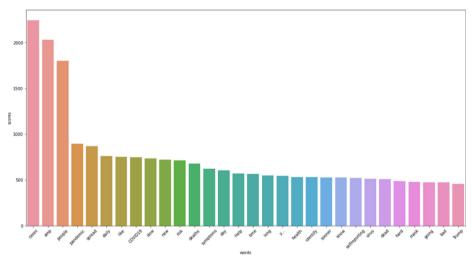


Fig. 8. Sentiment Analysis for Negative Words.

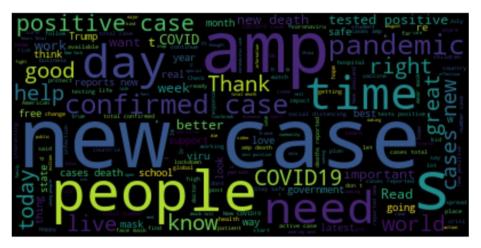


Fig. 9. Word Cloud for positive words.



Fig. 10. Word cloud for negative words.

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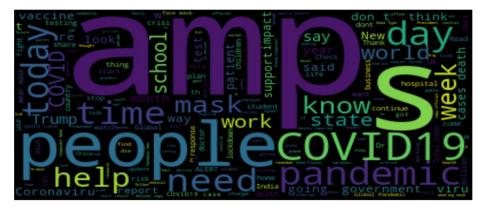


Fig. 11. Word cloud for neutral words.

5. Conclusion

Throughout the text, the importance of social network analysis is discussed. Twitter is a popular social media platform where people can express themselves and share their thoughts. This study employed over 370 tweets from Twitter to do emotional analysis for three key phrases connected to the COVID-19 pandemic (COVID, CORONA VIRUS, and COVID – 19)." The results were presented in this research. Positive tweets account for approximately 31% of total tweets, whereas negative tweets account for approximately 19% of total tweets. This means that half of all neutral tweets on Twitter, or half of all tweets based on these respective terms, are neutral in their attitudes. In the COVID situation, neutral sentiments outweighed both positive and non-positive sentiments, according to the polarity analysis.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

- [1] S. Aliza, C. Nadam, S. Basr, Twitter sentiment analysis, in: In Proceedings of the 6th International conference on Information Technology and Multimedia, 2014, pp. 212–216.
- [2], Retrieved June 22 (2020), from ttps://en.wikipedia.org/wiki/COVID-19_pandemic_in_India.
- [3] J. Samuel, G.G.M.N. Ali, M.M. Rahman, E.k. Esawi, Y. Samuel, Ek Esawi, and Yana Samuel, "Covid-19 public sentiment insights and machine learning for tweets classification.", Information 11 (6) (2020) 314.
- [4] https://en.wikipedia.org/wiki/COVID-19_pandemic_in_India.
- [5] J. Samuel, G.G. Ali, M. Rahman, E. Esawi, Y. Samuel, Covid-19 public sentiment insights and machine learning for tweets classification, Information 11 (6) (2020) 314.
- [6] A.P. Patel, A.V. Patel, S.G. Butani, P.B. Sawant, Literature Survey on Sentiment Analysis of Twitter Data using Machine Learning Approaches, IJIRST-International journal for Innovative Reasearch in Scinece & Technology, (10) 2017..

- [7] Bagheri, H., & Islam, M. J. Sentiment analysis of twitter data. arXiv preprint arXiv:1711.10377.
- [8] H. Saif, Y. He, M. Fernandez, H. Alani, Contextual semantics for sentiment analysis of Twitter, Inf. Process. Manage. 52 (1) (2016) 5–19.
- [9] Wang, X., Wei, F., Liu, X., Zhou, M., & Zhang, M. Topic sentiment analysis in twitter: a graph-based hashtag sentiment classification approach. In Proceedings of the 20th ACM international conference on Information and knowledge management, 2011, pp 1031-1040.
- [10] R. Singh, R. Singh, A. Bhatia, Sentiment analysis using Machine Learning technique to predict outbreaks and epidemics, Int. J. Adv. Sci. Res 3 (2) (2018) 19–24.
- [11] F.B. Hamzah, C. Lau, H. Nazri, D.V. Ligot, G. Lee, C.L. Tan, M.K.B.M. Shaib, CoronaTracker: worldwide COVID-19 outbreak data analysis and prediction, Bull World Health Organ (2020) p. 1(32).
- [12] B. Liu, Sentiment analysis and subjectivity, Handbook of natural language processing 2 (2010) 627–666.
- [14] Yaqub, U., Sharma, N., Pabreja, R., Chun, S. A.Atluri, V., & Vaidya, J. Analysis and visualization of subjectivity and polarity of Twitter location data. In Proceedings of the 19th Annual International Conference on Digital Government Research: Governance in the Data Age 2018, p. 1-10.
- [15] S. Ayvaz, M.O. Shiha, The effects of emoji in sentiment analysis, Int. J. Comput. Electr. Eng. (IJCEE.) 9 (1) (2017) 360–369.
- [16] M. Meduru, A. Mahimkar, K. Subramanian, P.Y. Padiya, P.N. Gunjgur, Opinion mining using twitter feeds for political analysis, Int. J. Comput. (IJC) 25 (1) (2017) 116–123.
- [17] G. Angiani, L. Ferrari, T. Fontanini, P. Fornacciari, E. lotti, F. Magliani, S. Manicardi, A Comparison between Preprocessing Techniques for Sentiment Analysis in Twitter, In KDWeb (2016).
- [18] A. Ramsden, A. Bate, Using word clouds in teaching and learning, Retrieved on 1 (2008 September) 2013.
- [19] P.E. Touchette, R.F. MacDonald, S.N. Langer, A scatter plot for identifying stimulus control of problem behavior, J. Appl. Behav. Anal. 18 (4) (1985) 343– 351.
- [21] K. Sai Prasad, Dr. S Pasupathy, P.Chinnasamy, A.Kalaiarasi(2022). An Approach to Detect COVID-19Disease from CT Scan Images using CNN - VGG16 Model . 2022 International Conference on ComputerCommunication and Informatics (ICCCI), Jan. 25 – 27, 2022, Coimbatore, INDIA.

Further Reading

- [13] V.S. Jagtap, K. Pawar, Analysis of different approaches to sentence-level sentiment classification, International Journal of Scientific Engineering and Technology 2 (3) (2013) 164–170.
- [20] K.R. Moon, D. van Dijk, Z. Wang, S. Gigante, D.B. Burkhardt, W.S. Chen, K. Yim, A.V.D. Elzen, M.J. Hirn, R.R. Coifman, N.B. Ivanova, G. Wolf, S. Krishnaswamy, Visualizing structure and transitions in high-dimensional biological data, Nat. Biotechnol. 37 (12) (2019) 1482–1492.