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Twitter Sentiment Analysis during the Lockdown on New Zealand

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***Abstract*—**One of the most common fields of natural language processing (NLP) is sentimental analysis. The inferred feeling in the text can be successfully mined for various events using sentiment analysis. Twitter is viewed as a reliable data point for sentimental analytics studies since people are using social media to receive and exchange different types of data on a broad scale during the COVID-19 epidemic. The processing of such data may aid in making critical decisions on how to keep the situation under control. The aim of this research is to look at how sentimental states differed in a single geographic region during the lockdown at two different times.1162 tweets were analyzed related to the COVID-19 pandemic lockdown using keywords hashtags (lockdown, COVID-19) for the first sample tweets were from March 23, 2020, until April 23, 2020, and the second sample for the following year was from March 1, 2021, until April 4, 2021. Natural language processing (NLP), which is a form of Artificial intelligent was used for this research to calculate the sentiment value of all of the tweets by using AFINN Lexicon sentiment analysis method. The findings revealed that the sentimental condition in both different times during the region's lockdown was positive in the samples of this study, which are unique to the specific geographical area of New Zealand. This research suggests applied machine learning sentimental method such as Crystal Feel and extended the size of the sample tweet by using multiple tweets over a longer period of time.

***Keywords*—**Sentiment analysis, Twitter analysis, lockdown, Covid-19, AFINN, NodeJS.

I. Introduction

RECENTLY, the Coronavirus epidemic has forced several policy reforms and has had a significant impact on the decisions made to remedy the situation. The lockdown decisions to deter the virus's dissemination were among the most crucial of these decisions. The COVID-19 pandemic has now affected over 200 nations, regions, and territories [1]. As a consequence, a survey of public opinion is required to assess people's reactions to a such incident. Opinion mining, commonly known as sentiment analysis is the interpretation of people's feelings, sentiments, perceptions, behaviours, and reactions about things like goods, programmes, organisations, persons, problems, events, concerns, and their characteristics [2]. However, a significant amount of data is provided by social website users plays an important role in decision-making [3]. The popularity of social media, such as Twitter, has sped up the exchange of information and expression of views on current affairs and health crises [4]. Social media have become useful platforms for accessing people's thoughts and comments on a variety of subjects [5]. As a result sentiment analysis has become a central component of social media science [2]. Because in these platforms, people can openly share their opinions on a variety of topics, products, and politics [6]. Therefore, recognizing people's reactions towards this danger may offer valuable insight in how culture behaves and reacts to unwelcome and unforeseen circumstances, and may be constructive or harmful. According to Merchant and Lurie [7], analyzing public reactions will better explain how the public's expectations and perceptions shift after a pandemic, which has a gradual impact on person and collective health. As a result, the emphasis of this research is on addressing the following question:

Q: what is the variation in public sentiment state during the lockdown period in two separate periods of the pandemic in a particular zone like New Zealand?

The study utilized Twitter, a common microblogging site, to develop a lexicon-based sentiment analysis model for classifying "tweets" into positive and negative sentiment. Polarity identification, or deciding whether the emotion conveyed in a text is positive or negative, is the most common application of sentiment analysis.[8]. Methods for detecting polarity divided mainly into machine learning-based, lexicon-based [6]. The lexicon-based sentiment analysis was used for this analysis. Because of their unsupervised existence and ease of use, lexicon-based sentiment analysis methods like AFINN have become widely common [9]. However, In this research, Twitter data was used to discover the difference in the sentimental state of people during the lockdown in the state of New Zealand during two separate years of the COVID-19 crisis, specifically on the first lockdown which was at the beginning of the crisis 2020 and the lockdown that occurred recently in 2021. The importance of such an analysis is crucial because it influences decision-making. To devise strategies and treat patients, lawmakers and health providers must consider the experiences of ordinary citizens on what causes them discomfort, distress, and trauma [10]. Data were analysed sentimentally by quantifying this sentiment with a positive or negative value, which is known as polarity by using the AFINN lexicon technique depends on the NodeJS JavaScript.

The remainder of the paper is planned out as follows: Section 2 begins with an overview of previous literature, which is divided into two parts first part: Overview of people perception towered COVID-19, second part: Lockdown perception. Section 3 explains the research methods; Section 4 presents the findings with a discussion; Section 5 describes the research limitations; and finally, Section 6 conclusions.

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II. Literature Review

One of the emerging research areas is sentiment analysis using social media data. Sentimental analysis is a form of machine learning that involves identifying expressions of the author's opinion-based attitudes that are reflected towards individuals through natural language processing. [11]. Natural Language Processing (NLP) attempts to derive a more complete context predictor from a text, attempting to determine who, when, where, how, and why a certain action was taken [12]. The polarity of the data is calculated in sentiment analysis by classifying the tone of the data as positive, negative, or neutral. The Twitter dataset contains a large amount of recent data on user behaviour, feelings, and thoughts in r elation to current affairs around the world [13]. It is more relevant because it could play a vital role in medical crises such as the COVID-19 pandemic. While many studies on sentiment classification and NLP from different perspectives is still ongoing, the following are some of the connected researches.

A. Overview of People Perception toward COVID-19

The research goals and methods varied in the studies. Much of the literature on sentimental analysis of Twitter data currently pays special attention to analyse the overall global situation towards the COVID-19 pandemic and specifically analysing the most important topics discussed by users on social media platforms during the crisis. Boon-Itt and Skunkan [14], conducted a study to understand the main pandemic discussion among Twitter users and identify the main public concerns and topics posted by English users by employing NLP for sentimental analysis. One of the main findings was the negative perception of the COVID-19 from people generally. In the same vein, Xue, Chen, Hu, Chen, Zheng, Su and Zhu [15], analysed Twitter data to explores the world sentimental state for 8 emotions across 13 topics. The predominant sentiments for the spread of COVID-19 were anticipation that steps could be taken, particularly for the lockdown and spread of the virus, followed by mixed feelings of anger, and fear related to various topics such as new cases, death, and quarantine. Likewise, researchers used the algorithm CrystalFeel to examine patterns in four emotions: anxiety, rage, sadness, and joy, which were obtained from 20 million worldwide English tweets between 28 January 2020 and 9 April 2020. In the early stages of the COVID-19 pandemic, emotional trends emerged. When the virus first appeared at the end of January, anxiety was the primary emotion. As the crisis progressed, anxiety became less prominent, with less than 30% of regular tweets in early April[16]. However, Chakraborty, Bhatia, Bhattacharyya, Platos, Bag and Hassanien [17], in their research found that the overall sentential state for the Twitter was positive towered COVIDe-19. Although, the majority of tweets about COVID-19 were optimistic, netizens were preoccupied with retweeting the negative ones. The sample tweet was obtained between 28 January 2020 and 1st July 2020 by the researchers. They used the LDA algorithm to categorise each tweet with seventeen latent semantic attributes linked to ten detectable topics and seven latent sentiment attributes obtained by the CrystalFeel algorithm. They discovered that the most common emotion expressed in tweets was anger [18].

Up to now, a number of studies reported that the overall emotional state ware negative towered the pandemic. Praveen and Ittamalla [19] studied Twitter data aimed at defining the overall global response to the COVID-19 crises as well as identifying the core concerns people discussed. They identified general global trends in the first five months of the pandemic, which were neutral. However, regarding the concerns that shaped this situation, the researchers in this study divided the hubs into four main categories: crisis severity, precautionary measures, lockdown, and personal life. They found that the high number of cases infected with the virus, which falls under the severity of the crisis, caused great concern among users. Along the same line, Garcia and Berton [20] found that about every subject was influenced by negative emotions. Their purpose in this paper is to compare English and Portuguese languages using topic modelling and sentiment analysis methods on COVID-19 Twitter data. Proliferation care, case reports and statistics, economic consequences, politics, treatments, entertainment, and sports are some of the topics that are similar in both languages. During the COVID-19 pandemic, negative feelings dominated almost every subject in English. In Portuguese, the words "proliferation treatment," "case reports and statistics," and "education and community" all had negative connotations. The sentiments are almost similar when it comes to "economic impacts " [20]. Fig. 1. a scheme showing the polarity of the sentimental state towards the COVID-19 and the methods used in the analysis.

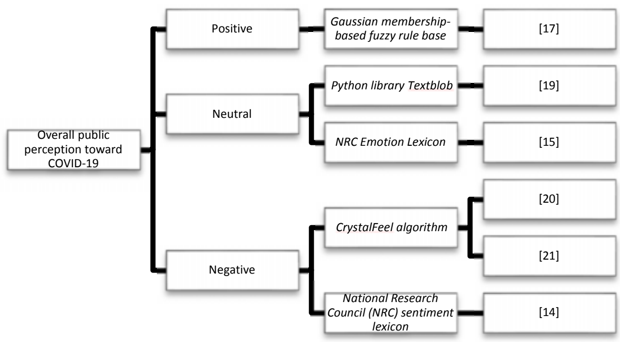

Fig. 1 A diagram illustrating the polarity of the sentimental situation toward the COVID-19 and the research methodologies

B. Lockdown Perception

Globally, the impact of lockdown decisions on the general emotional state has been investigated using Twitter data samples. Some studies have shown in their analyses that lockdown was one of the most significant issues that were discussed during the crisis, as well as some studies have shown the general impact of the quarantine on the users. Researchers conducted this analysis to learn more about Indian residents' feelings about the government's national curfew. the data collected by using Tweepy API and processed through the Python tools [21]. Lockdown was one of the most important topics that were debated during the crisis [21]. Statistically, they found that almost half of the selective sample tweets showed a positive sentiment about the lockdown. While less than a quarter showed a negative feeling[21]. Similarly ,according to Boon-Itt and Skunkan [14], one of the most common public issues and subjects discussed on Twitter by English users was lockdowns. Furthermore, the researcher discovered that public opinion of the lockdown remained optimistic. As more facts became available as the outbreak progressed, public sentiment turned to a more positive note. [14]. In the same line , according to Xue, Chen, Hu, Chen, Zheng, Su and Zhu [15], one of the most popular terms shared by users are lockdown and quarantine, indicating that it is one of the most significant topic discussed among users. However, a study conducted by Imran, Daudpota, Kastrati and Batra [22] , aimed to look at how civilians from various cultures reacted to the novel Coronavirus and how people felt about subsequent behaviour taken by various countries, in order to gauge both positive and negative feelings about the COVID-19 lockdown. Deep long short-term memory (LSTM) models were used to estimate sentiment polarity and emotions by the researchers. They discovered that both positive and negative feelings were similarly prevalent when it came to #lockdown; however, the average number of positive tweets was higher than the average number of negative tweets in Pakistan, Norway, and Canada [22].

Recent research focuses on people's opinions during the COVID-19 widespread Lockdown impact in India [23].The outcomes revealed that Lockdown received the most positive feedback [23]. However, other studies looked at how Twitter tweets contributed to public opinion on quarantines placed across the world as a result of the pandemic. Karami and Anderson [24], goal is to identify anti-quarantine comments on the social platform. The authors use a Twitter platform to collect the data and then applied the LAD algorithm for data modelling to identify 11 different topics. The main finding of the study was the most arguable topic about the order of governors to close businesses and impose self-quarantine. The users argued that the quarantine against people's liberty and freedom. Followed by the topic related to the negative effects on peoples' mental health because of the quarantine [24]. Likewise, the theme of lockdown and its consequences were listed in some studies that categorised the most relevant topics using the LDA algorithm. The overall reaction to the lockdown was negative, and the economic effect of the lockdown was negative [19]. Fig. 2 shows a public concern and sentiment toward "lockdown".

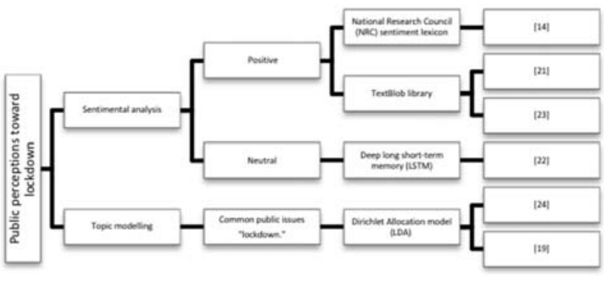

Fig. 2 Schema shows public attitudes toward lockdown in terms of sentimentally polar analysis and topic modeling method

III. Method

The methods approach employed in this study is illustrated in Fig. 3. The remainder of this section contains more information about this illustration.

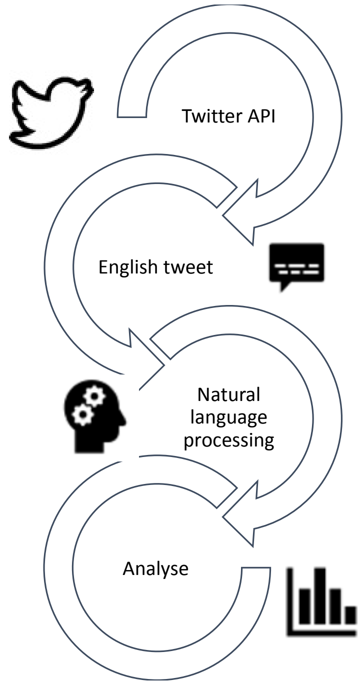

Fig. 3 The workflow of the methodology

A. Data Collection

Detecting COVID-related tweets allows researchers to get a better understanding of the general public's feelings and concerns about the crisis [19]. Many scholars have used data from the Twitter platform to perform an insight study in order to better understand public perceptions of emerging social problems including COVID-19, such as the wearing of masks [25] or vaccine for COVID-19 [26]-[28].

However, Twitter allows researchers to gather data via the public streaming Twitter application programming interface (API). For this study Twitter has utilised as a tool to collect data using specific queries and hashtags of ‘lockdown’, ‘COVID-19’and ‘corona viruses. The fetching dates have set for the first sample from March 23, 2020, until April 23, 2020, and the second sample for the following year was from March 1, 2021, until April 4, 2021. It's crucial to pick this time frame because on March 23, the New Zealand government declared a level 3 lockdown, requiring people to stay at home to prevent any chance of outbreak. This was the country's first lockdown due to COVID-19. However, For the second time zone that was in the following year and after the return to normal life in the region, the lockdown in that year was March 1, 2020, until April 4, 2020.A total of 1162 tweets were collected containing tweet IDs, tweets, dates. For the first sample the number of tweets was 580 while the second sample 582 tweet.

B. Sentimental Analysis

The most common utilization for NLP is sentiment analysis. Sentimental analysis is the method of analyzing data and determining the sentimental score of that data is positive, negative, or neutral. The information may be a single word, a statement, or an entire text. Sentiment analysis is described as "the automatic method to extract and analyze the subjective judgments on different aspects of an item or entity" [29]. A lexicon-based sentiment analysis technique which is AFINN Lexicon was used in this analysis .Researchers mentioned that the AFINN lexicon is one of the simplest structures and is a widely used lexicon [30]. The disadvantage of using a dictionary-based lexicon, according to Feldman [31], is that it is general and does not allow for domain-specific detail. Fig. 4. represents the process of sentiment analysis by using the AFINN lexicon.

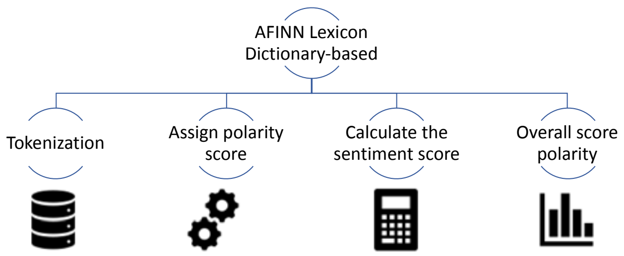

Fig. 4 Sentiment analysis process using the AFINN lexicon

1. Data Pre-Process

A Node Puppeteer library, which provides a high-level API to monitor Chrome or Chromium over the DevTools Protocol, was used to pre-process the data. Puppeteer library that split the phrases into single words. Rapidapi is used to retrieve tweets which is unstructured data. The data was then sorted into a JSON-formatted database. Then this is done by storing the data in arrays that divide the tweets into words, and each word is stored independently to facilitate dealing with it in the process of analysis and classification. The process of breaking down a string into its single word is called "tokenisation". The overall token words or emojis found in the input string for this analysis for both years 2020 and 2021 is described in Fig. 5.

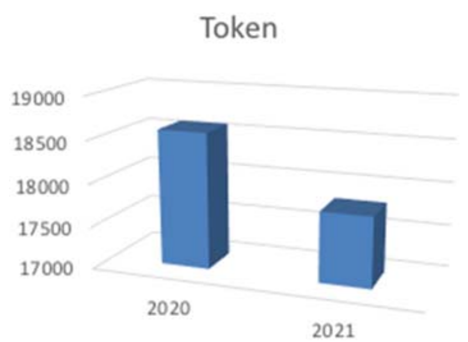

Fig. 5 Shows the number of token words and emojis from tweets for both sample 2020 and 2021

The dataset (token) entered into the AFINN-based sentiment analysis for Node.js. However, the AFINN-165 wordlist and Emoji Sentiment Ranking to perform sentiment analysis on arbitrary blocks of input text by assigned a numerical value between -3 (negative) and 3 (positive). The tokenization will be matched against this set, and the integer value for each one will be stored; in this analysis, the polarity of the expression will be determined by the weighted average of the scores. To decide the overall sentiment of the text, the scores of all recognised words are added together. A text analysis generates a total sum of each word's worth (referred to as a "score") or a score separated by the number of words in the message (referred to as "comparative"). If both positive and negative terms are present in the language, the outcome will be neutral. This can be seen in the outcomes of a Fig. 6 example analysis for score calculation for words and emojis.

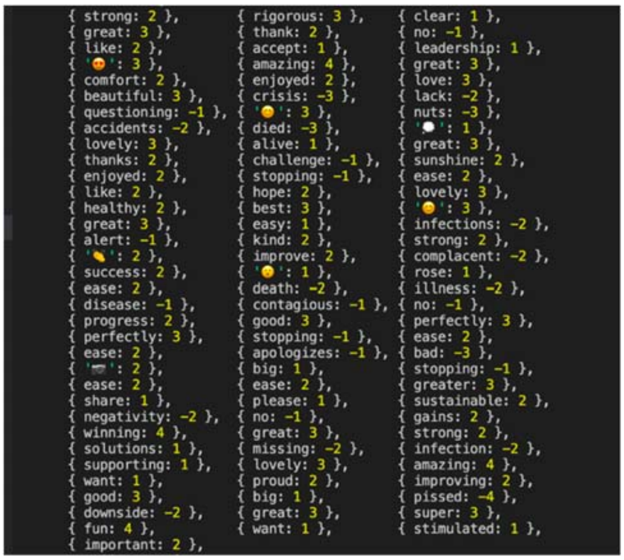

Fig. 6 Example score calculation analysis

2. Polarity Results

The sentiment analysis library will return six possible score of polarity and emoji 3 (very positive), 2 (positive), 1 (less positive),0 (Neutral and None no polarity is detected), -1 (less negative), -2 (negative) , -3 (very negative). These polarities determine the sentiment of tweets. Fig. 7. explains the process of computing the final sum of the polarity analysis in the process of sentiment analysis in sample tweet.

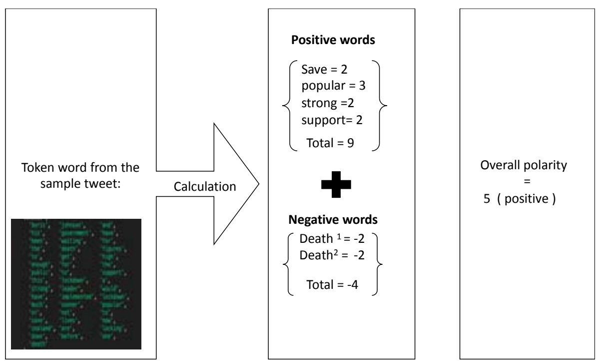

Fig. 7 Polarity analysis explanation

IV. Findings and Discussion

A. Results

This study found no significant differences in people's opinions about lockdown decisions due to the COVID-19 pandemic in two periods of time, particularly between the commencement of the pandemic in 2020 and the subsequent lockdown decision in the following year 2021. At the beginning of the crisis in the year 2020, the total number of words that have feelings, in general, was less than the total words contained in the tweets in the closing decisions in the following year, 2021. However, the total number of words in the sample in the year 2020 represents 951, while in the year 2021 the number is higher, which is approximately 1138. Fig. 8 shows the statistics for the two samples.

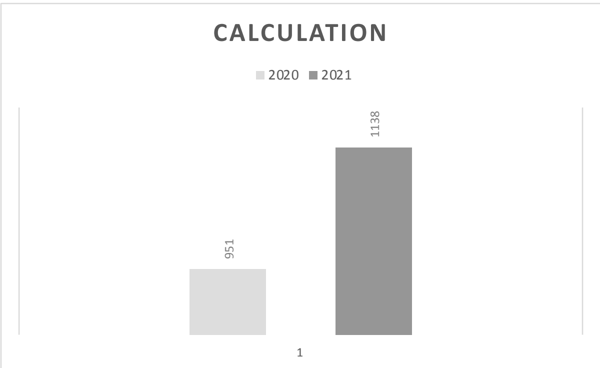

Fig. 8 Statistics for the both samples

The percentage of positive terms that hold positive emotions in tweets in general during the shutdown periods in the area was higher by a significant level and a large gap in 2020, with positive words accounting for approximately 71 percent of the overall, whereas negative words account for approximately 29 percent. Fig. 9 represents the percentages for both negative and positive words for year 2020.

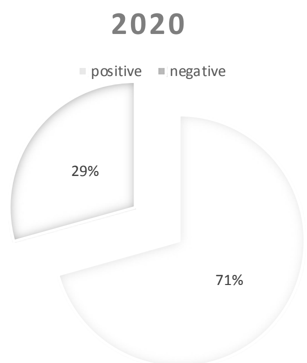

Fig. 9 The positive and negative word on tweets for year 2020

In the following year, which is 2021, during the total closure of the region, another sample was taken for comparison, and the results in this sample indicate that the positive words found in the tweets were 61% higher, compared to the negative words in the tweets, which accounted for 31%. Fig. 10. shows the percentages for both negative and positive words for year 2021.

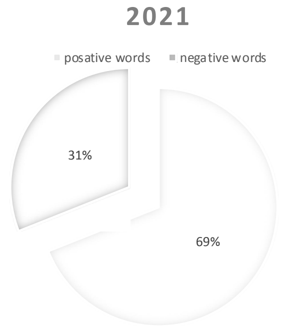

Fig. 10 The positive and negative word on tweets for year 2021

Taken together, these results suggest that, in general, for all the two years, the positive situation in both years during the closing periods was positive, but at the beginning of the crisis the percentage of the positivity among users was higher by nearly 2%.

V. Discussion

This work analyzes tweets related to sentiment state related to COVID-19 lockdown via the Twitter considering users' locations primarily in a specific region which is New Zealand.

Thanks to the accuracy of the tweet's metadata, researchers may be able to peer at emotions and emotional discrepancies and explore cultural differences [32]. The results of this study reveal that in both the period's March 2020 and March 2021, New Zealand Twitter users exchanged positive terms at a rate of roughly 71 % and 61 %, respectively, implying that the overall sentiment situation was generally favorable during the lockdown. As a result, it could be worthwhile to investigate the importance of emotion intensity scores and their patterns over time, frequency [32]. However, owing to a lack of sampling size to accurately assess the sentiment state for specifically user's locations remains difficult to evaluate. In the same line Tsai and Wang [33], because of the lack of this detail in most users' accounts, tweets relating to COVID-19 user's locations were not included in the study. However, Praveen and Ittamalla [19] reported the response of public to the lockdown was not optimistic. In their research, they used a random sampling of tweets from around the world. Which is more likely to produce different outcomes when deciding a certain location. The sample used for this analysis was tweeting from a specific location, New Zealand, and it precisely measures the sentimental state of Twitter users in that audience. The result of this research indicate to the positivity among the users was higher during the two different periods of the lockdown on the area which probably it indicates acceptance in general. Such sort of analysis could be useful to examine public mental well-being and other areas such as Media and communication research and psychology [32].

VI. Limitations

For two factors the research sample was insufficient to determine the precision of the polarity of the positions:

– The first is that there is a time limit.

– The second factor is the lack of popularity of Twitter as a communication platform in the target audience which influences the sample size for selected tweets. According to Hinton [34], YouTube and Facebook are the most used social media platforms in New Zealand, with 87 and 83 percent of the population using each channel, respectively. While Twitter users account for approximately 27% of the population, it is the least popular social media platform in the area.

VII. Conclusions and Future Work

The study of a Twitter dataset about current events, such as COVID-19, is being used as a gauge of the general public's condition. The use of nostalgic terms by users in their posts shows a region's overall polarity state. This will assist policymakers in assessing the situation in the event of a disease outbreak and devising a response strategy. The aim of this paper is to examine how people reacted during the lockdowns into a separate time of the pandemic. The research's primary objective is to use natural language processing methods to determine whether public opinion score is positive or negative. The key result of this study indicates that the overall sentimental analysis score for the attitude condition for the chosen region is favorable in both periods. However, in future work, the study will concentrate on improving strategy by tackling the problem of sample size and integrating scores from various models.

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