Sentiment Analysis of Lockdown in India During COVID-19: A Case Study on Twitter

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Abstract

As when the number of individuals using the Internet has skyrocketed in recent years, recommendation system has emerged as one of the most prominent areas of research in natural language processing (NLP). By using sentiment analysis, the unstated feelings contained within the text may be mined in an efficient manner for a variety of purposes. During the COVID-19 eruption, a significant number of people are use various forms of social media to both receive and distribute various sorts of information. The evaluation of people's feelings gleaned by mining such material may be a crucial component in the decision-making process for maintaining command of the situation. The purpose of this research is to have a better understanding of how Indian individuals feel about the statewide lockdown that has been imposed by the Indian government in an effort to slow down the pace at which Coronavirus is spreading.

In this study, natural language processing (NLP) and machine learning classifiers were used to conduct sentiment analysis on tweets that were submitted by Indian residents. It was determined that there were a total of 12,741 tweets using the phrases "Indialockdown" during the dates of April 5 and April 17, 2020. Data have been retrieved from Twitter and used the Tweepy API, annotated utilising the TextBlob as well as VADER lexicons, and highly processed utilising the natural language tool package that is made available by Python. In order to categorise the data, we used a total of eight distinct classifiers. With the Linear SVC classifier using unigrams, this experiment was able to obtain the greatest accuracy possible of 84.4%. According to the findings of this poll, the majority of Indian residents agree with the choice of the Indian government to execute a shutdown during in the coronal outburst. One and a half months later, on March 11, 2020 COVID-19 is classified as pandemic [4]. Coronavirus disease (COVID-19) is an infective pandemic caused by a newly discovered virus named Corona. Most of the formidable diseases are generated from unhygienic habits.

Hygiene measures and sanitation, such as hand washing, could play an important and cost-effective role in reducing the spread of pandemics, such as the COVID-19 [5]. The disease causes respiratory illness (like the flu) with symptoms such as cough, fever, and in more severe cases, difficulty breathing. Mostly, the symptoms in the person infected with COVID-19 are low to medium respiratory illness and recover without any specific treatment. Aged persons and those already having some medical issues like chronic respiratory disease, diabetes, cancer, and cardiovascular disease are more vulnerable to acute infection from COVID-19. We can protect ourselves by avoiding touching our faces, washing our hands frequently, and avoiding close contact (1 m or 3 feet) with the unwell people. The most likely ways of spreading COVID-19 are the following: direct contact with an infected person; contact with the droplets of a virus carrier; or direct touch of contaminated objects or surfaces with COVID-19 virus, and then rubbing the nose or touching the mouth [6]. At this time, there are no specific vaccines or treatments for COVID-19, and this new pandemic creates fear for the world because of its estimated mortality rate of 2%–5% [7].

The most cost-effective ways to become safe are precaution and social distancing in the absence of vaccination for this infectious disease. Social distancing is a crucial way to limit the *spreading of the COVID-19 pandemic, where different physical distancing restrictions are applied to fight against COVID-19 [6]. People are advised to stay at their homes and to ensure social distancing almost all the countries enforced lockdown to ensure social distancing at public places. In the history of human civilization, these times were never experienced where the whole world has been residing under lockdown [8]. Lockdown is an exigency protocol that forbids people from moving freely in public places. A total lockdown means people must stay wherever they are and not even go outside their building. We can understand lockdown as the curfew with some relaxation to essential services. All non-essential services are closed for the full lockdown period. More than 200 countries, areas, and territories are rapidly impacted by the COVID-19 pandemic [9]. Being the most affected country in the month of March 20, Italy enforced a nationwide lockdown on March 9, 2020.*

I. INTRODUCTION

Initiated in Wuhan, China, the explosive spread of Coronavirus illness (COVID-19) has generated a public health disaster not just in the surrounding area but also globally [1]. On January 20, 2020, the Emergency Operations Center (EOC) of the Centers for Illness Control and Prevention (CDC) was activated, and the World Health Organization (WHO) issued its first report about the situation related Coronavirus disease 2019 (COVID-19) [2]. The new Coronavirus was identified by the WHO and given the name "2019-nCOV" to describe it. Prior to January 20, 2020, when the National Health Commission (NHC) formally classified it as a B-type infectious illness and began taking efforts to combat this pandemic, the severity of the COVID-19 pandemic had been understated.

The World Health Organization (WHO) subsequently declared the situation to be a global health emergency on January 30, 2020. After that, almost every one of the nations afflicted by COVID-19 put their country on lockdown in an effort to stop individuals from coming into intimate touch with one another and, as a result, stop the virus from spreading. The Indian government was quite well aware that extreme measures were required to be taken in India to start reducing the rapidly with increasing growing amounts of COVID-19 infections, recovered cases, and death cases after looking at the numbers of COVID-19 cases that occurred in China, the United States of America, Britain, Italy, and other countries [10]. This stage was launched by the government of India with a lockdown that lasted for one day, beginning on March 22, 2020, and continuing for a total of 21 days, beginning on March 25 and ending on April 14, 2020. In light of the favourable outcomes of lockdown 1.0, India has decided to carry it over into the second phase, which will last until May 3, 2020.

There are significant obstacles to be overcome in practically every nation on the planet when it comes to the deployment of preventative measures [11] in an effort to curb the spread of the Coronavirus. Even though instituting a lockdown is the only approach, until a vaccine against COVID-19 can be developed, to slow the pace at which it spreads, it has resulted in some major problems for every country, such as a decline in the economy and, therefore, in GDP. Workers who are paid an hourly salary are having a difficult time making ends meet as a result of the closure of industries. This leads to an increase in irritability and, as a consequence, depression because of factors such as unemployment, freedom, isolation, and the lack of additional medical services, amongst other things. In general, everyone agrees with this choice; nevertheless, owing to these difficulties, various individuals have varying perspectives regarding whether or not a lockdown should be imposed throughout the country.

Because of the fast transmission of the Coronavirus, there is an urgent need for the development of quick analytical methods [12] that can evaluate the information flow and the development of public opinion in a variety of pandemic scenarios. This opens up the possibility of doing research on how the general public feels about the choice at hand, which is also the impetus for this body of work.

The technique of determining the feelings that are conveyed by a set of words is referred to as sentiment analysis. It is possible to characterise it in a broad sense as the process of appointing opinion categories and scores in accordance with a keyword and phrase, which are then matched with sentiment score lexicons and individualised dictionaries [12]. It is a subfield of text mining that involves the processing of natural language in order to automate the process of extracting and categorising the feelings conveyed in written text.

This subfield of text mining is called emotion mining. The procedure assists in elucidating the writer's perspective with regard to any entity, issue, or product, for example. [13]. The examination of how the general population feels about the lockdown is crucial since it has an effect on how well this stage is completed. If for some reason the general population is unhappy with this choice, it will be very difficult for the government to accomplish what they set out to do during the lockdown. With 565 million people currently using the Internet [14], India is one of the largest consumer markets for digital products.

Therefore, using social media platforms is the greatest feasible option to get real writings produced by regular people. Due to the length restrictions imposed on messages, Twitter is the site that is most suited for carrying out sentiment analysis on written texts. Even social media platforms are being utilised by people, companies, and governments to interact with one another on a variety of significant events and health crises such as COVID-19. In light of this, the examination of such material may prove to be of utmost significance for the administration in the process of effectively choosing policies, and it may also assist health care organisations in determining the requirements of their stakeholders [15].

People are often utilising Twitter during this outbreak of COVID-19 to voice their ideas and to gain necessary information on the activities done by the government [16]. During this time, Twitter has become an important communication tool.

Fig-1: steps of NLP

In addition, there is a lack of information on the views held by the general public regarding the primary issues that have been the subject of debate throughout the course of time [2].

The categorising of feelings may be carried out through a variety of different methods. We may primarily divide these strategies into three categories, which are as follows: 1) a method that is based on lexicons; 2) an approach that utilises machine learning and deep learning; and 3) an approach that is hybrid. In this study, we have classified the viewpoint of India's common people using a method called machine learning. It is necessary to do data pre-processing on raw data before using machine learning for sentiment analysis.

This is because the effectiveness of the algorithm used is directly related to the quality of something like the training and testing datasets. Natural language processing is a kind of pre-processing that is used in the field of sentiment analysis (NLP). Tokenization, lemmatization, stemming, part of speech tagging, name entity identification, and chunking are the six processes that are included in this process [17].

II. A DISCUSSION OF THE LITERATURE

One of the most rapidly developing areas of study is sentiment analysis derived from data collected from social media. As a result of the fact that it has the potential to be very useful in the event of serious medical crises like as the COVID-19 pandemic, its significance has increased. Even though a significant amount of research on sentiment categorization and natural language processing (NLP) is currently being conducted from a variety of perspectives, some of the studies that have already been done are as follows:

To determine the number of cases in Wuhan between December 1, 2019, and January 25, 2020, Wu et al. [1] utilised data on the count of infected people exported from Wuhan from December 31, 2019, to January 28, 2020. These dates ranged from December 31, 2019, to January 28, 2020. Then, cases that were exported inside the nation were anticipated. They predicted the COVID cases across the country by using the flight booking data and COVID positive persons who travelled through flight. They also predicted the national and international spread of COVID-19 after calculating the impact of the metropolitanwide quarantine of Wuhan and surrounding cities that was started in China from January 23–24. This prediction was made after the COVID cases across the country were predicted using the flight booking data.

Medford et al. [2] retrieved tweets that were connected to COVID-19 and then assessed the frequency of terms that were related to infection preventive techniques, inoculation, and racial bias. They carried out a sentiment analysis in order to investigate the level of emotional valence and the predominant feelings. They carried out topic modelling in order to identify and investigate trending themes of conversation across time. They collected 126 049 tweets that were made by 53 196 unique people.

After the 21st of January in 2020, there was an abrupt surge in the number of tweets that were connected to COVID-19. The feelings range from dread, which was expressed by roughly half (49.5%) of all postings, to astonishment, which was expressed by about 30% of all posts. There was a strong correlation between the amount of racist postings and the number of new instances of COVID-19 positives. The implications of the COVID-19 on both the economy and politics were the most often brought up subjects of conversation.

The Weibo postings of 17,865 active users were gathered and evaluated by Li et al. [3] utilising online ecological recognition (OER), which was based on several machine learning prognostic models. They analysed the retrieved postings to determine the word frequency, emotion indicator scores (such as sadness, anxiety, anger, and happiness), and cognitive indicators (such as social risk assessment and life fulfilment).

Before and after the ratification of COVID-19 on January 20, 2020, they ran the opinion mining and the paired sample t-test in order to examine the differences within the same group. This was done so that they could determine whether or not there were any significant differences. According to their analysis of the data, the levels of sensitivity to social hazards and negative feelings have risen, whilst the scores of good sentiments and life enjoyment have fallen.

Pandey et al. [5] developed a model for life-long learning that gives authentic information in Hindi, which is the Indian language that is spoken most often in the country of India. This helped them bridge the gap between the information and the danger of inaccuracy. By using machine learning and natural language processing, they were able to match the sources of real and genuine information, such as the news supplied by WHO. They found that the combination that performed the best overall had a Cohen's Kappa of 0.54 and it was implemented into their application.

Kayes et al. [6] combed over one hundred thousand tweets from Australian users that had the hashtag #coronavirus. Out of these one million tweets, there are only 3076 that include the term "social distancing" or the hashtag #socialdistancing. They put 8000 tweets through the training and validation process, but just 2000 tweets are put through the testing phase.

They performed quite well on the test data, with an accuracy of 83.70% and an F1-score of 81.62%. They used the trained model to analyse all 3076 tweets that included the phrase "social distancing." They made the observation that more than 80 percent of the tweets that referenced "social distance" had a favourable attitude, as shown in the illustration. They came to the conclusion that people in Australia tolerated social distance and even supported it. [Citation needed]

Because of the extensive community quarantine that was in place during the COVID-19 epidemic, Pastor et al. [7] conducted a research to find out the students' perspectives on the online method of instruction delivery and to collect their feedback on it. In order to carry out this study, the researchers visited the Lingayen Campus of the College of Business and Public Administration (CBPA) at Pangasinan State University and solicited the feedback of the students there.

To begin, they sent out an email to all of the students, in which they asked them to respond to a few questions about potential difficulties that may arise during their time spent studying online. They discovered that the majority of the students had the perception that they would have some difficulties, and a significant number of them were concerned about the level of Internet access in the region. They came to the conclusion that the majority of students are not ready for the online delivery of instructions, and as a result, they suggested that educational institutes should offer students an alternative method of receiving instructions in order to keep the quality of education at a high level.

A research was carried out by Dubey et al. [8] with the purpose of contrasting the thoughts and feelings expressed in Indian and American tweets while the subjects discussed Narendra Modi and Donald Trump, respectively. Tweets were collected from April 1, 2020, all the way through April 9, 2020, for the purpose of opinion mining. The emotions and feelings expressed in these tweets have been analysed with the help of the NRC Emotion Lexicon. They came to the conclusion that favourable feelings were expressed in 64.53 percent of tweets referencing Narendra Modi, whereas just 48.71 percent of tweets mentioned Donald Trump.

During the epidemic, Chen et al. [9] conducted a research on the issue of the topic about the use of contentious and non-controversial phrases associated to COVID-19 on Twitter.

They utilised LDA to gather topics clusters from tweets collected from Twitter that were either contentious or not controversial, and then they qualitatively contrasted the subjects clusters via both sets of tweets.

Even after removing the keywords connected to the "Chinese virus" before the study, they found that the topics that were most prevalent in the controversial tweets were mostly associated with China. On the other hand, discussions that were present in the tweets that were not controversial were about dealing with and battling COVID-19 in the United States.

After the Indian government made the announcement about the lockdown, Barkur et al. [10] analysed the feelings of Indian residents. Twitter, a social networking tool, was used by them for the analytic process. They read through the tweets to get a sense of the general feeling among the Indians over the shutdown.

They collected the tweets from March 25, 2020, all the way through March 28, 2020, using the hashtags #IndiaLockdown and #IndiafightsCorona. Both of these hashtags were used extensively. They analysed 24,000 tweets for the purpose of the research by using the programme R, and they produced a word cloud that analyses the attitudes expressed in the tweets. They discovered that people were upset, afraid, negative, and disgusted as a result of the lockdown; yet, they also discovered that positive feelings were strongly included in the tweets. They came to the conclusion that Indians were resolute in their conviction that they had to slow the pace at which COVID-19 was spreading and were committed to doing so.

III. PROPOSED APPROACH

During the COVID-19 epidemic, we have presented a methodology for the examination of sentiments in this part. Figure 2 provides a visual representation of the framework. The following is an explanation of the many steps of the architecture that are required to carry out a sentiment analysis of lockdown when corona outbursts are occurring.

A. The Gathering of Data

During COVID-19, a sentiment analysis is carried out on the lockdown that would be enforced by the Indian government from March 25, 2020, all the way through April 14, 2020. As a result, the data that are particular to the target are not accessible; hence, we have generated the data set by hand. Since March 2020, there has been a significant rise in the number of people talking about the epidemic on social media [9].

This comes as a direct result of the worsening situation. Through the use of Tweepy, we were able to compile a list of 12 741 tweets that used the term "Indialockdown" during the dates of April 5 and April 17, 2020.

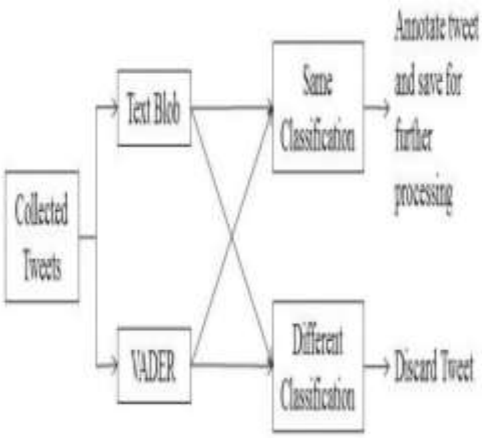

Fig. 3. Data annotation process.

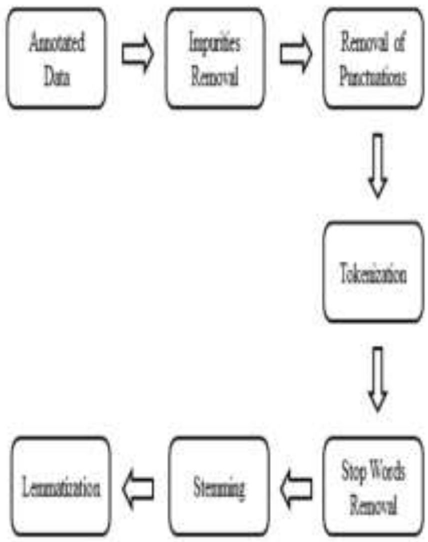

Fig. 4. Data pre-processing.

B. Data Labeling

Following the gathering of tweets, we categorised them according to whether they were good, neutral, or negative using the method shown in Figure 3. We have determined the polarity of each tweet by using the TextBlob library and the VADER (Valence Aware Dictionary for Sentiment Reasoning) function that is available in Python. In the subsequent step, we have consolidated the polarities by taking the intersection of the findings from TextBlob and VADER. Following this phase, we are left with 7284 tweets, of which there are 2097 tweets having neutral polarity, 3545 tweets with positive polarity, and 1642 twitter posts with negative voltage.

C. The Preprocessing of the Data

There is a possibility that the data we have acquired include unsought and sentiment-less terms such as links, Twitter-specific words such as hashtags (starts with #) and tags (starts with @), single-letter words, numerals, and other types of information. These kinds of words have the potential to take on the function of noise inside the training and testing of our classifier. Before incorporating information into the classifier, it is vital to clean the labelled data set of any noise in order to improve the performance of the classifier.

The labelled data set is isolated from the background noise by our pre-processing tool [21]. Figure 4 depicts the many stages of the pre-processing phase.

After converting the data set together into data frame, we then removed string punctuations, tokenized it, and removed English stop words, stemmed, and lemmatized it. Finally, we developed a module to remove the impurities that were stated above in this stage.

D. Vectorization

The machine learning classifiers are only able to process input that is in the form of numbers and not in any other language. Consequently, in order to make use of the text data for predictive modelling, it is necessary to first turn it into features. In order to determine the frequencies of individual words, we made use of the CountVectorizer learning algorithm. CountVectorizer generates a sparse matrix by calculating the number of times each word in the text is used and then displaying the results.

E. Providing Instruction and Exercises to the Classifiers

Following the extraction of features from the pre-processed data set, we have sent the data on to be classified by machine learning algorithms. In order to do this, we have made use of a total of eight different classifiers, which are as follows: Multinomial Naive ayes, Bernoulli Naive ayes, Logistic Regression, LinearSVC, AdaBoostClassifier, Ridge Classifier, PassiveAggressiveClassifier, and Perceptron. We trained the classifiers using 80 percent of the data and tested them with 20 percent of the data. We have determined the effectiveness of the classifiers described earlier by using 1-g, 2-g, and 3-g respectively.

F. Experimental Setup

All of the tests are carried out on a Python 3.0 platform with a core i3 CPU that is 2.4 GHz and has a 3 MB L3 cache. Additionally, there is 4 GB of RAM. Python source code for the experiment was written using the Anaconda integrated development environment. We extracted tweets using Twitter's "Tweepy" API, and we preprocessed the data using the natural language toolkit (NLTK) package in the Python programming language. In addition, the Matplotib, Pandas, Numpy, and Sklearn libraries are used during the course of this study.

IV.RESULTS AND DISCUSSION OF THE DATA

In this part, the result analysis of all of the classifiers based on accuracy, precision, recall, F1-Score, and receiver operating characteristics (ROC) curves with various grammes has been described. These metrics were used to evaluate the performance of the classifiers. In addition to this, we have verified our data set for each model using the k-fold cross-validation procedure with k equal to 10. This was done using unigrams, bigrams, and trigrams.

The accuracy of a classifier may be determined by using (1) and (2), which is one of the numerous metric units that are used to evaluate classifiers. It is calculated by taking the ratio of the number of accurate predictions to the total number of forecasts.

Accuracy may be calculated as the ratio of the number of right forecasts to the total number of predictions.

Regarding the technical side of things, we are able to comprehend accuracy in terms of positives and negatives asAccuracy is calculated by dividing the number of true positives and true negatives by the total number of forecasts (2)

		Actual Class	
		Positive	**Negative**
Predicted Class	**Positive**	True Positive	False Positive
	Negative	False Negative	True Negative

Fig. 5. Pictorial representation of positives and negatives.

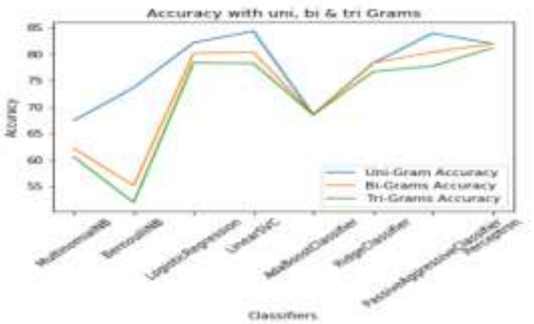

Fig. 6. Comparison of accuracies with uni-, bi-, and trigrams.

Model using a limited quantity of the available input data. Using this methodology, the data set is partitioned into k equal parts, also known as folds. After that, any one fold is selected at random to be used as a testing set, while the remaining k1 folds are utilised for the purpose of training the model. Finally, the pass score for this specific permutation is recorded.

This procedure is carried out k times, with each new fold serving as a testing set and the remaining folds serving as training sets. The final score of a model's cross-validation is found by taking the mean of all of the permutations' scores and dividing it by the total number of possible combinations. Unigrams, bigrams, and trigrams were used in the calculation of each model's cross-validation score. Using the LinearSVC classifier, we were able to get the maximum possible cross-validation score of 0.85 with the unigram, 0.82 with the bigrams, and 0.8 with the trigrams.

Other measures to use in the evaluation of the models include precision, recall, and F1-score. The percentage of positive identifications that really belong to the positive class is referred to as precision, and it may be determined using the following formula: (3). The recall percentage may be determined using formula (4), which reveals the number of properly detected positive predictions relative to the total number of positive cases. The F1-Score, which is calculated by multiplying precision by recall and dividing by five, is the weighted harmonic mean.

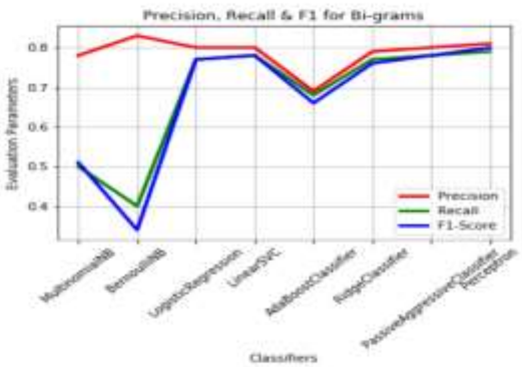

Fig. 7. Tenfold cross-validation score comparison between unigram, bigrams, and trigrams.

Recall may be calculated as true positives divided by true positives plus false negatives. (4) F1 − Score = 2 ∗ (Precision ∗ Recall)/(Precision + Recall). (5) We have evaluated all of the classifiers by comparing their accuracy, recall, and therefore their F1-score with unigrams, bigrams, and trigrams respectively.

V RESULTS AND ANALYAIS

Following an analysis of the accuracies, precision, recall, F1-Score, and k-fold cross-validation scores of eight distinct classifiers using unigram, bigrams, and trigrams, we found that LinerSVC with unigram produced the best results. After then, we checked that it was still accurate by examining the confusion matrix and AUROC curves associated with our model.

Therefore, using this combination, we projected a total of 7071 tweets, and after analysing them, we discovered that 48.69% of people are talking positively about the lockdown, 29.81% of people are indifferent, and 21.5% of people are feeling negatively due to some cause, as shown in Figure 14.

The findings are in line with our predictions, since the vast majority of people are in favour of it due to the fact that lockdown may be the most effective preventative step in this life-threatening epidemic. Additionally, individuals need to communicate with one another since any potentially dangerous circumstance might arise at any time.

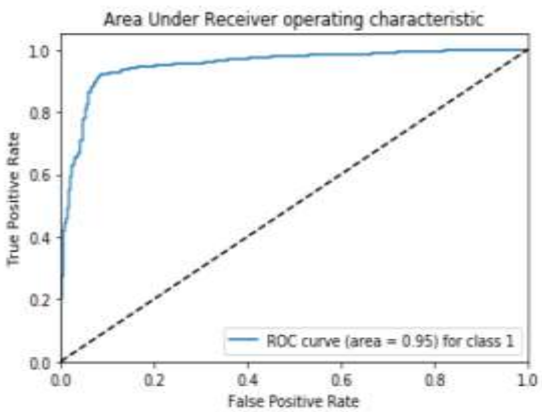

Fig-8:AUROC curve for positive class.

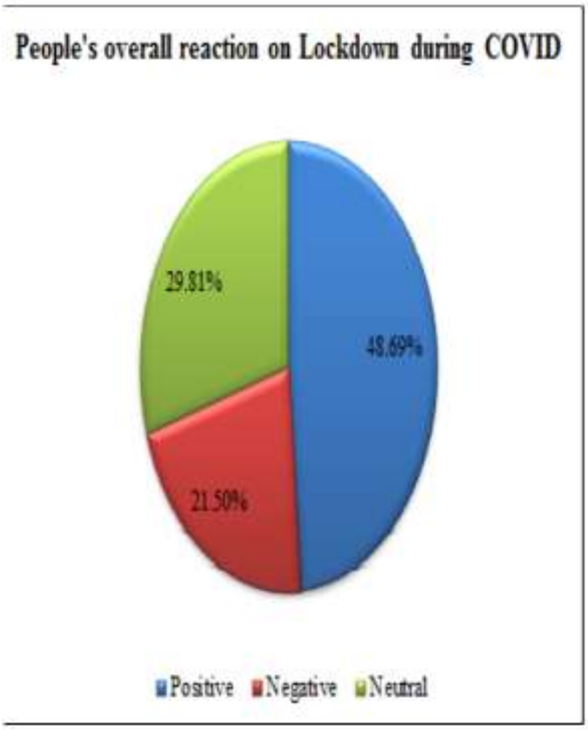

Fig-9: People reaction on lockdown in India.

Since there are many rumours, which is the primary reason why there is a certain quantity of neutral tweets, and because we have previously given many different grounds for bad feelings; thus, some of the sentiments are also negative.

Output screens

Fig-10: Home page

Fig-11: View all Retweets

Fig-12: Tweet Name

Fig-13: Users posts

VI. CONCLUSION

The number of people using social media platforms skyrockets every single day. This trend is only expected to continue. People are more likely to reveal their unfiltered thoughts on social media as opposed to speaking their minds directly to another person.

We analysed the responses of the general people as a whole on Twitter to determine how they felt about the lockdown that was imposed by the Indian government during the outbreak of COVID-19. We gathered tweets throughout phase 2 of the lockdown that was implemented in India because we were motivated by the varied comments that came following the announcement of the lockdown. Following annotation as well as data transformation, we sent the gathered data through 8 different controlled machine learning approaches to see how they perform with various grammes of text.

The LinearSVC classifier and the unigram seem to have the greatest performance, according on our observations. The combination provides us with an accuracy of 84.4%, making it the most accurate combination out of all of the combinations that we have tried out on our data set. We have improved the performance by doing calculations on accuracy, recall, F1-score, and tenfold cross-validation for each of the possible combinations. LinearSVC and unigram produced the best results for us in this regard. Consequently, we put this combination to use in order to conduct the sentiment analysis on the tweets that were being sent out by the public during the lockdown, and we discovered that nearly half of the population (48.69%) is talking positively about the lockdown, while 29.81% of the people are remaining neutral, and 21.5% of the people are feeling negatively due to some reason. Our model has undergone further analysis, which included looking at the confusion matrix and the AUROC curves.

In general, it can be seen that Indians have embraced the battle against the pandemic in a good manner, and the majority of the public supports and agrees with the decision made by the government to impose the lockdown in order to lower the pace at which the disease is spreading. The fact that the lockdown has been met with favourable feedback suggests that India has been successful in thwarting the exponential spread of the Coronavirus to a significant degree [10]. These kinds of activities might be of use to policymakers and health care agencies as well in times of public health catastrophes like the COVID-19 outbreak.

Sentiment analysis of natural languages in and of itself contains a broad scope to work on, and as a result of health emergency, this work is also expressed with a wide variety of potential future scopes to work on.

The tweets made before the first lockdown began and those sent after it was lifted may be analysed in forthcoming research to reveal how people's feelings changed throughout each incident and how those shifts were related to the outcomes of those incidents. The factors that can affect mental stability during pandemics can also be studied, and the study of the impact of fake news on the public can also play an important role in assisting the administration and policymakers in controlling the situation [10]. Both of these studies have the potential to play an important role in the control of the situation. When it comes to the technological side of things, future research might look at ways to make the model more accurate while also conducting experiments on a big corpus.

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