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Emotional Analysis of Indian Twitter Messages During the COVID-19 Pandemic

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Abstract—

The area of natural language processing known as sentiment analysis has recently surpassed all others in importance and popularity. Sentiment analysis is a tool for extracting emotions from text. In the midst of COVID-19, everyone is utilizing social media to spread and receive information. Authorities in charge of making decisions benefit from the assessment of such material. This study employs Natural Language Processing and Machine Learning algorithms to examine Indians' feelings during the Lockdown. To get data from Twitter, we utilize the Tweepy API. To annotate it, we use the TextBlob and VADER libraries. We use NLTK to preprocess the data. Ensemble model with unigram delivers strong performance, according to the experimental data. The majority of Indians support the government's decision to implement a lockdown, according to polls.

Index Terms—COVID-19, Lockdown, Machine learning, Natural language processing, NLTK.

INTRODUCTION

Originating in Wuhan, China, the COVID-19 pandemic quickly spread around the globe. The virus that caused the sickness known as Covid-19 was SARS-CoV-2. The sickness allegedly originated at a Wuhan seafood market. Because it targets the respiratory system specifically, the illness poses a significant threat to human health. Lost sense of smell and taste are the primary signs of the illness. There were several efforts to contain the epidemic before it spread, but none of them were successful. After the first confirmed case in China, steps were made to contain the virus, including screening all foreign flights. The rate of transmission of the COVID-19 pandemic is increasing at an alarming rate. This made disease management a major challenge. This led to an exponential growth in the number of reported cases over time. It was observed that the current active number of cases is exactly related to the pace of increase in COVID-19 cases. Thus, it took some time after its genesis for it to become a worldwide epidemic. No one kind of the sickness has been identified. Alpha, gaama, delta, BF.7 India manjubalabisi@nitw.ac.in, and omicron are just a few of the known variations of the COVID-19 virus. Because of this, it became challenging to design vaccinations, since certain vaccines worked against some variants but not others. Since the human immune system is unable to combat delta, it was determined that this variation was the most lethal of the bunch. After each wave, the number of active cases drops dramatically until the next one arrives. To combat this contagious illness, social isolation became essential. The only way to contain the epidemic was to isolate people socially, using measures like quarantine and lockdown. A lot of people were for lockdown and a lot of others were against it. Proponents of lockdown measures recognized that quarantine is crucial in the battle against the virus and in preserving lives. The demographics, population density, and economics of a nation are other factors that significantly impact the decision to implement a lockdown. Consequently, gathering people's opinions and perspectives becomes crucial. In the event of a future epidemic, the government may benefit from data analyzing public mood. A collection of tweets from Indian residents on the nationwide lockdown to manage the coronavirus crisis is one of the main goals of the work. Using five categories—"very positive," "moderately negative," "neutral," and "highly negative"—to analyze user attitudes using various machine learning models and evaluate their effectiveness. Here is how the remainder of the paper is structured: Section II discusses related work. In Section III, the suggested method is detailed. The outcomes of the experiments are discussed in Section IV. The article is concluded in Section V.

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RELATED WORK

Since the majority of people express their opinions on social media, sentiment research on these platforms may be quite beneficial. Emotional analysis is the subject of much current study across several disciplines in an effort to ascertain public opinion. The frequency of terms like racial partiality, inoculation, and preventative techniques in tweets connected to COVID-19 is estimated in [1]. We collected the tweets of 53,196 unique people, totaling almost 126,000. From January 21, 2020, forward, there is an increase in tweets on COVID-19. Half of the postings were filled with dread, while a third were filled with astonishment. Active COVID-19 positives were shown to be inversely linked to the amount of racist postings. Financial and political ramifications of the COVID-19 pandemic were among the most talked-about issues. In [2], the feelings and thoughts of people in the US and India are examined. The collection of tweets took place from April 1, 2020, to April 9, 2020. The NRC Emotion Lexicon was used to get opinions from the general public. No less than sixty percent of the tweets about the prime minister of India are complimentary. Regarding the US Prime Minister, almost half of the people felt positively about it. An analysis of the feelings of people from various nations towards the COVID-19 is presented in [3]. After cleaning the tweets, an LSTM model was used to determine their emotional content and polarity. It was discovered that only few nations supported a full quarantine. In [4], a Naïve Bayes method was used to manually categorize 10% of the data gathered from January to March 2020 and identify tweets connected to COVID-19 as either positive or negative. Using social media data, academics have been able to better understand how people feel about a product, event, or issue in recent years [5]- [6]. In [7], remote supervision is used to do sentiment analysis on tweets. As a kind of background noise, we trained on tweets that included emoticons. The models were constructed using the Naive Bayes classifier, Maximum Entropy (MaxEnt), and Support Vector Machine (SVM). Bigrams, unigrams, and POS were their characteristics. Use of a support vector machine (SVM) model with unigram data outperforms alternative combinations. A lot of people have believed false notions and gotten their news wrong about the epidemic [8]. According to recent research, Twitter is a great place to do sentiment analysis. In [9], we can see the many methods and instruments needed to do modulated analysis. Data annotation is made easier using Textblob and Vader. To quantify user sentiment, VADER was used in the study [10]. Health organizations' postings in [11] [12] were used to forecast the future pandemic crisis. In order to make accurate predictions, data was quickly gathered from many sources. Researchers looked at the use of social media during the COVID-19 outbreak in [13]. Among the tweets, only one percent came from reputable sources like journalists or physicians. It was determined that around 16% of the tweets were deceptive, and that approximately 84% of the tweets included unreliable medical information. In order to get to the heart of the message, sentiment analysis is crucial.

PROPOSED APPROACH

The structure for the suggested method to examine attitudes on Twitter data during the COVID-19 outbreak is shown in Fig. 1. During the Corona epidemic in India, we used this approach to do sentiment analysis of the lockdown.

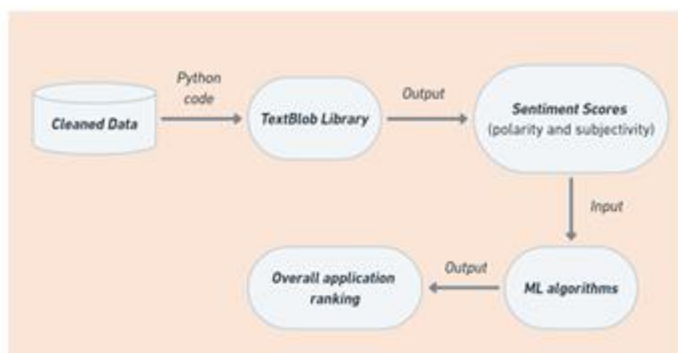

Fig. 1. Framework for Sentiment analysis

Section A. Data Migrating From March 25, 2020, until April 14, 2020, the Indian government instituted the COVID-19 lockdown, and sentiment analysis was conducted on the subject. Due to the lack of relevant objective-specific data, we had to manually assemble the data set. As the situation has worsened since March 2020, there have been a lot more remarks on the epidemic on social media. From April 5, 2020, to April 17, 2020, we gathered over 10,000 tweets using the hashtag "#Indialockdown" using the Tweepy API.

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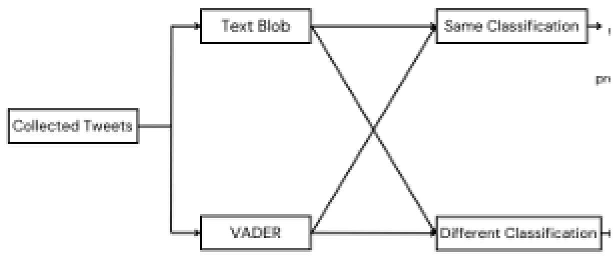

Fig. 2. Data annotation process

B. Annotating Data Following the steps outlined in Figure 2, we sort the tweets into five categories: very positive, somewhat positive, neutral, somewhat negative, and very negative. This is done after we have extracted data from Twitter and collected tweets. To do this, we use the TextBlob and VADER libraries to assign various polarity to all of these tweets. The polarities are then solidified by taking the intersection of the TextBlob and VADER findings. Discarded from further processing are the tweets with different polarity findings.

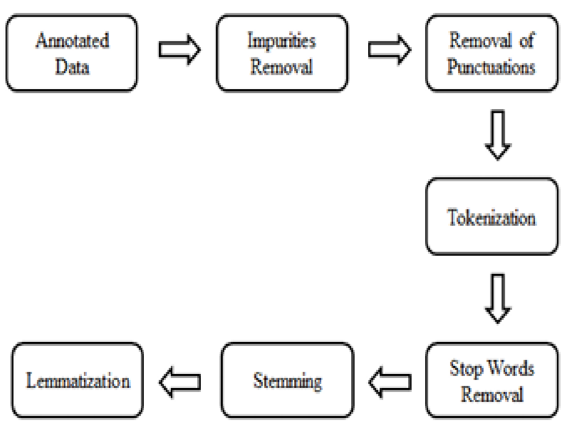

Fig. 3. Data preprocessing

C. Pre-processing of Data We cannot guarantee that the data we gather is free of typos, grammatical errors, unicode characters, links, hashtags, tags (which begin with the letter "@"), numerals, and punctuation. These terms have the potential to introduce noise into our classifier training and testing processes, which might lead to inaccurate model outputs. Eliminating background noise from the labeled data set is an important step toward making classifiers more efficient. Figure 3 shows the processes that a pre-processing module takes to clean the data set of contaminants. Here, we use a module to get rid of all those pesky pollutants. After finishing up with the data pre-processing, we turn it into a data frame and then remove punctuation, stop words, stemming, lemmatization, tokenization, and the operations associated with it. D. A Vectorization Model Numerical data is the sole input that machine learning models will take. As a result, turning the text input into numerical values is essential. We determine word frequencies by using the extractor's Count Vectorizer function. Here we can see the sparse matrix that Count Vectorizer, which counts how often each word appears in the text, produces.

TABLE I EXAMPLE MATRIX FOR COUNTVECTORIZER

Index	0	1	2	3	4	5	6	7	8
Doc1	1	1	1	2	1	1	1	1	1

"His friend went out shopping with his brother and sister," Doc1 says, just as an example. Our vectorization library, CountVectorizer, will do the following to transform this text into a sparse matrix with an alphabetical word index: The number of occurrences of "his," "friend," "went," "out," "shopping," "with," "brother," "and," and "sister" is 3, 2, 0, and 5, respectively. Classifier Training and Testing (E) Machine learning models are fed the data after feature extraction. Logistic Regression, Bernoulli Naive Bayes, AdaBoost Classifier, Perceptron, Multinomial Naive- Bayes, LinearSVC, Passive Aggressive Classifier, Ridge Classifier, and the Ensembled model are the eight machine learning classifiers that we have used in our study. We trained the classifiers using 80% of the data and tested them using 20%. The aforementioned classifiers' performance has been evaluated using uni-gram, bi-gram, and tri-gram.

METHODS AND OUTCOME OF EXPERIMENTS

Here we have covered the various metrics, such as accuracy, precision, recall, and F1-Score, and how they are used to evaluate the results that the classifiers provide. Using the k-fold cross-validation approach (k=10), the data set was validated using

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unigram, bigram, and trigram. True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) are the four possible outcomes in the confusion matrix. Below you can find the performance metrics that were used in this project: Precision: It is defined as the proportion of accurate predictions to the total number of forecasts. First, the formula for accuracy is (TP + TN) divided by (TP + TN + FP + FN) (1). The number of accurate affirmative predictions is indicated by the precision parameter: The formula for precision is TP divided by the sum of TP and FP. two (2) Parameter "recall" indicates how many out of every 100 positive instances in the data a classifier accurately predicted. Recall is equal to TP divided by the sum of TP and FN (3). The F1-Score is the harmonic mean of the recall and accuracy scores. F1-score is 2 times the product of Precision and Recall divided by the sum of Precision and Recall (4). A. Scores from Cross-Validation Here we compare and analyze the models' acquired cross-validation scores for unigram, bigram, and trigram. Table II shows that in the Unigram scenario, the Perceptron model has the highest cross-validation score of around 0.68. Following Perceptron, the Ensembled model and the Ridge Classifier both have cross-validation scores of about 0.66. Additionally, only the highest cross-validation scores are being provided by Per ceptron for bigrams. For

TABLE II CROSS VALIDATION SCORES OF THE MODELS FOR UNI, BI AND TRI-GRAMS

Models	Uni-Gram	Bi-Gram	Tri-Gram
Logistic Regression	0.65	0.56	0.54
Bernoulli Naive-Bayes	0.56	0.52	0.52
Adaboost Classifier	0.58	0.56	0.53
Perceptron	0.68	0.58	0.54
Multinomial Naive-Bayes	0.60	0.51	0.50
LinearSVC	0.66	0.56	0.54
Passive Aggressive	0.66	0.56	0.54
Ridge Classifier	0.66	0.57	0.54
Ensemble Model	0.66	0.56	0.54

The ensemble model, Logistic Regression, Perceptron, Ridge Classifier, LinearSVC, Passive Aggressive, and trigrams all have almost identical cross-validation scores of 0.54. Precision (B) This section discusses the accuracy scores, execution time, and rank of each model that was considered for unigram, bigram, and trigram. Unigram Accuracy: 1) Unigram model rank, execution duration, and accuracy are shown in Table III.

TABLE III ACCURACY, EXECUTION TIME AND RNK OF THE MODELS FOR UNIGRAM

Models	Accuracy(%)	Execution Time(sec)	Accuracy Rank
Logistic Regression	68.5	28.9305	6
Bernoulli Naive-Bayes	62	3.36085	9
Adaboost Classifier	63.5	80.6551	8
Perceptron	70.5	6.82662	3
Multinomial Naive-Bayes	66.0	2.35138	7
LinearSVC	70.5	1.68393	2
Passive Aggressive	69	16.0927	5
Ridge Classifier	70	4.23037	4
Ensemble Model	72	48.5128	1

Unigram execution time for LinearSVC is at least 1.68 seconds. Out of all the models, the Ensemble Model has the highest accuracy at 72%. The order of importance is determined by the execution time of the Perceptron and LinearSVC models, both of which have substantial accuracy. The accuracy scores for each model for bigram are shown in Table IV, which pertains to 2) Bigram Accuracy. Using bigram, LinearSVC requires a minimum of 2.09 seconds to run. With a score of 61.5%, Passive Aggressive outperforms all other models. In terms of accuracy (61%), the Perceptron, LinearSVC, Ridge Classifier, and Ensemble Model models are very identical; the only differentiating factor is the amount of time it takes to run each model. Table V displays the accuracy, execution time, and rack for each model that utilizes trigram. Out of all the models, Adaboost Classifier has the highest accuracy rate.

Table iv ACCURACY, EXECUTION TIME AND RANK OF THE MODELS FOR BIGRAM

Models	Accuracy(%)	Execution Time(sec)	Accuracy Rank
Logistic Regression	60.5	78.02	6
Bernoulli Naive-Bayes	55.5	8.815	8
Adaboost Classifier	60	431.51	7
Perceptron	61	7.74	3
Multinomial Naive-Bayes	54.5	2.44	9
LinearSVC	61	2.09	2
Passive Aggressive	61.5	24.699	1
Ridge Classifier	61	10.305	4
Ensemble Model	61	37.3381	5

TABLE V ACCURACY, EXECUTION TIME AND RANK OF THE MODELS FOR TRIGRAM

International journal of applied exercise physiology

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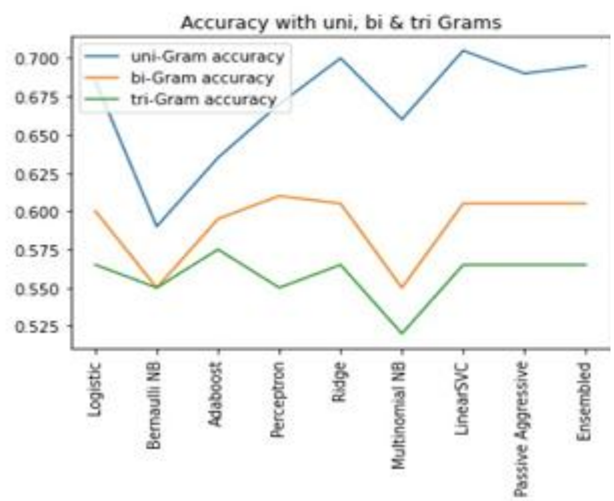
Vol-14 Issue-01 June 2025

Models	Accuracy(%)	Execution Time(sec)	Accu Ra
Logistic Regression	57	53.89	5
Bernoulli Naive-Bayes	55.5	18.15	8
Adaboost Classifier	58	266.14	1
Perceptron	56.5	8.982	7
Multinomial Naive-Bayes	52	2.89	9
LinearSVC	57	2.24	2
Passive Aggressive	57	24.88	4
Ridge Classifier	57	17.58	3
Ensemble Model	57	58.26	6

utilizing trigram, with a 58% success rate. Similarly, the accuracies of the Logistic Regression, LinearSVC, Passive Aggressive, Ridge Classifier, and Ensemble models are 57%, and the order of these models is determined by the amount of time it takes to run.



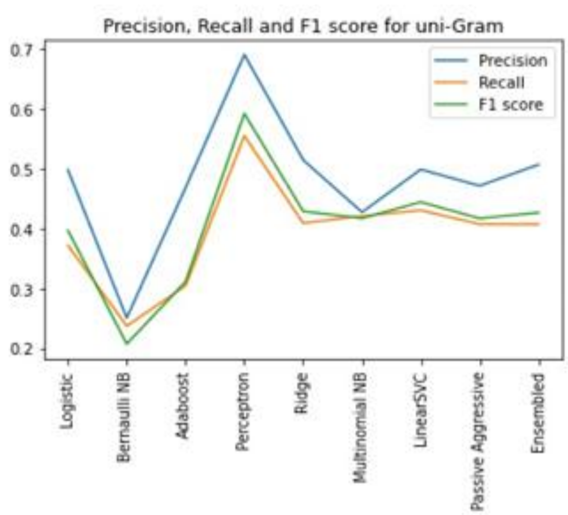


Fig. 5. Precision, Recall and F1 score for uni-Gra

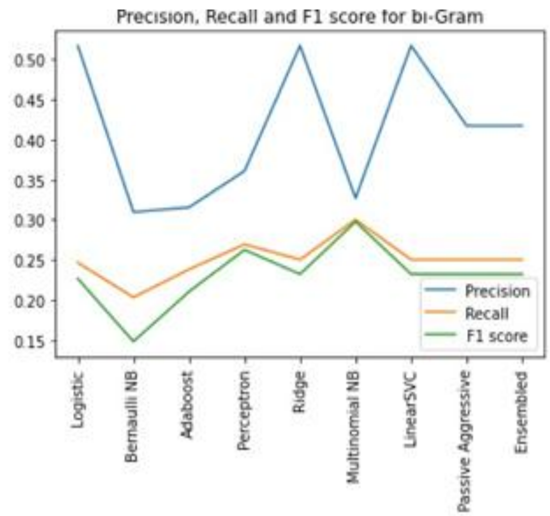


Figure 6 shows the Precision, Recall, and F1 score for the bi-Gram measure for all eight models. Figures 4–7 show the results for the N-gram models. The Ensemble Model is the most accurate of the Unigram models. In terms of accuracy, both the Perceptron and LinearSVC models are on par. Unigram models consistently outperform bigram and trigram. With the exception of Bernoulli-NB and multinomial-NB, all models are almost equally accurate for bigram. The most accurate model for Trigram is Adaboost. The Ensemble Model is the best option for analyzing sentiment during the COVID-19 lockdown because unigrams are more accurate than bigrams and trigrams. When comparing Unigram models, Perceptron outperforms the others in terms of F1-Score, Precision, and Recall. The Logistic Model is the most accurate Bigram model. After the Logistic Model and before Bernaulli-NB, the ridge and linear SVC models are similarly accurate, with the latter ranking last. Should the situation

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Vol-14 Issue-01 June 2025

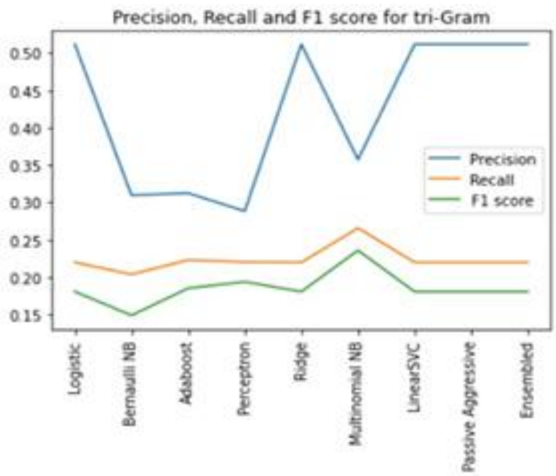

Figure 7: tri-Gram's Accuracy, Recall, and F1 Score Ensembled classifiers, Bernoulli NB, Trigram, and Logistic models all achieve similar levels of accuracy, while Perceptron achieves the lowest. When it comes to trigram models, the values of Recall and F1-Score are almost identical, and the values of both scores are quite low. The Multinomial-NB model outperforms all others in terms of Recall and F1-score.

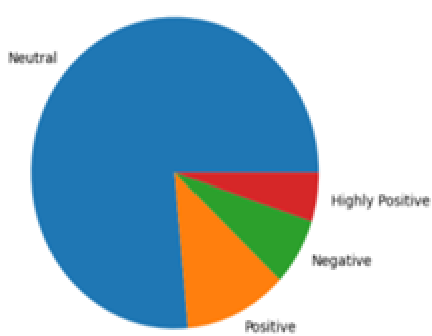

Fig. 8. Distribution of People Perception Towards LockDown

C. Determining from the data In this study, we compared eight distinct models using unigram, bigram, and trigram data. Unigram ensemble models outperform other types of models. In Fig. 8, we can see how the ensemble model and unigram feature extraction distributed the public's impression of the lockdown during COVID-19 in India. Among those who have expressed their opinions on the lockdown, 5.0% are very favorable, 12.0% are positive, 76.5% are indifferent, and 6.5% are negative. All signs point to a lockdown being necessary. The majority of individuals feel neither negative nor good about the shutdown. Few individuals are opposed to the lockdown because of many factors, such as financial concerns, rumors, etc.

CONCLUSION

The best and simplest method for people all around the globe to engage with one other and share their opinions on COVID-19 is via social media. We have compiled the tweets in order to study the perspective of Indians on the shutdown. We have used many machine learning algorithms to do sentiment analysis. With an accuracy of 72%, the Ensemble model and unigram were determined to be the most effective. Using this combination, we were able to forecast how the public will feel about the lockdown via tweets and discovered that 76.5% of people are ambivalent about it, suggesting that people are still on the fence about it. Only 5% of the population is strongly in favor of the lockdown, and 12% are strongly in favor of it; these individuals are certain that the only way to stop the spread of the coronavirus is to implement the lockdown. Almost 6.5% of the population is opposed to the lockdown for various reasons, including rumors, financial concerns, and food shortages. Not many individuals are totally against the lockdown—in fact, they're very negative about it. Local administration might benefit from improved performance on Lockdown data using various deep learning models; this would allow them to better manage rumors and make appropriate judgments during future pandemics.

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