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Sentiment Analysis of Tweets During the COVID-19 Pandemic Using Multinomial Logistic Regression

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ABSTRACT

Recently, the research on sentimental analysis has been growing rapidly. The tweets of social media are extracted to analyze the user sentiments. Many of the studies prefer to apply machine learning algorithms for performing sentiment analysis. In the current pandemic, there is an utmost importance to analyze the sentiments or behavior of a person to make the decisions as the whole world is facing lockdowns in multiple phases. The lockdown is psychologically affecting the human behavior. This study performs a sentimental analysis of Twitter tweets during lockdown using multinomial logistic regression algorithm. The proposed system framework follows the pre-processing, polarity and scoring, and feature extracting before applying the machine learning model. For validating the performance of proposed framework, other three majorly used machine learning based models-- namely decision tree, naïve Bayes, and K-nearest neighbors-- are implemented. Experimental results prove that the proposed framework provides improved accuracy over other models.

KEYWORDS

Covid-19, decision tree, K-nearest neighbors, lockdown, Multinomial Logistic Regression, Naïve Bayes, pandemic, sentiment analysis

INTRODUCTION

Covid-19 an ongoing global pandemic disease is caused by a novel coronavirus. It has sensationally affected human life in the entire world and given challenges to the global health system, societal system, economy, work culture etc. Many countries have applied lockdown to prevent the spread of coronavirus disease. Lockdown smashes the monitory and social disturbance among people as they have been locked in their homes and can move only for essential services. Many of the studies reported the psychological impact of lockdown on human behavior like anger, sorrow, depression, frustration etc. (Balhara et al., 2020; Kantermann, 2020; Kumar & Dwivedi, 2020; Prati & Mancini, 2021; Bera et al., 2021). All these behaviors adversely impact the health of a human being. The dynamics

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of Covid-19 comprising mortalities, number of daily cases, number of active cases, aftereffects of coronavirus on patients, impact on children etc. has been shared by people on the social media during severe pandemic (Hussain, 2020; Goel & Gupta, 2020; Gao et al., 2020).

The current pandemic has changed the way of living, behaving, and communicating with each other all around the world (Hung et al., 2020; Zang, 2021). These specific circumstances have raised the challenges of movement of data while educating, working, and communicating online in the public arena. The pandemic due to Covid-19 has also brought a genuine challenge for governments, businessmen, associations, and media to improve the existing systems to control the virus spread. The current crisis is globally forming a socially advanced situation due to lock on the free movements during relocation, travel among states, travel among nations, number of gatherings in events and many more. Now, every movement of people is dependent on Information and Communication Technology (ICT).

ICT has supported people to communicate through social media platforms to share their thoughts and emotions during this corona outbreak. Twitter is one of the social media platforms which is majorly used by people for distributing and getting information. Plenty of information is available on twitter in the form of tweets. By analyzing these tweets one can determine the state of mind (happy, bad, depressed, frustrated etc.) of people during lockdown. By knowing the state of mind of people, government and other social groups can help them to bear the pandemic. In this work, we have considered the large dataset of tweets for sentiment analysis on textual data on Covid-19. In open literature, some of the studies suggested making use of machine learning techniques to improve the performance of sentiment analysis. As per our knowledge, no one has applied the multinomial logistic regression algorithm for performing the sentiment analysis on Covid-19 data. However, the technique is used for other datasets. This study aims to propose a framework using multinomial logistic regression to perform sentiment analysis on Covid-19 twitter data.

Rest of the paper was organized as follows: Section 2 discusses the background and literature review. Section 3 introduces the proposed system framework adopted for the current work. Section 4 discusses the multinomial logistic regression algorithm in detail followed by result and discussion in section 5. Section 6 concludes the present study followed by future work.

Acronyms Used

BERT: Bidirectional Encoder Representations from Transformers
LR: logistic regression
SVM: Support Vector Machines
LSTM: Long-short Term Memory
NLP: Natural Language Processing
RF: Random Forest
ML: Machine Learning

BACKGROUND AND LITERATURE REVIEW

The pain and fear due to Covid-19 are still all around the world (Ahorsu et al., 2020) News regarding pandemic like causalities, shortage of health systems etc. have dominantly outstripped other news on social media. Many of the studies in open literature presented sentiment analysis concerning different applications. Few of the works are summarized in Table 1. However, such news sometimes includes fake and unproven news due to biasness of people. Therefore, there is always a need to systematically determine the negativity due to Covid-19 news time to time using sentimental analysis.

Twitter is leading another social media for collecting the information either health-related or other (Saad and Yang, 2019). Number of studies presented the sentimental analysis based on the twitter tweets. Barker and Vibha (2020) presented the sentiment analysis on Covid-19 pandemic for India. In the study they used a set of 24000 tweets. In another study, Li et al. (2020) focused on the psychological impact of pandemic on the human behaviour. Authors claimed increase in depression level due to pandemic among the people. One of the studies even reported industrial crisis due to this pandemic. They also discussed the emergence of new opportunities (Kaushik & Guleria, 2020; Fernandes, 2020). Cinelli et al. (2020) presented the analysis on the data from various social media platforms. The experimental results reported the faults in the accumulated information. In one of the studies, authors discussed the classifiers for short and long text information. They concluded both Naïve Bayes and LR works better for short text as compared to long text (Samuel et al., 2020). Another study detected emotions on the similar approach for short and long text messages (Kleinberg et al., 2020).

Number of other research presented sentiment analysis using machine learning approaches. Xue et al. (2020) did analysis on 4 million tweets using Latent Dirichlet Allocation (LDA) to identify sentiments in the tweets. Li et al. (2020) claimed that depression is the major emotion among the people due to work from home, loss of job and fear. Many of the people are using emojis on social media to reflect their emotions. One of the studies presented a BERT model to consider emojis for emotion analysis (Feng & Zhou, 2020).

Number of studies applied the deep learning approaches in the open literature. One of the studies used NLP for finding the essential issues due to Covid-19 pandemic on social media platforms (Jaloder et al., 2020). They used the LSTM model to perform the sentimental analysis. Imran et al. (2020) performed the sentimental analysis on Covid-19 tweets using deep learning. Sanders et al. (2020) done analysis of tweets to determine the public attitude towards the mask during pandemic. In another study, authors presented sentimental analysis for two intervals. Authors reported neutral and negative polarity for the first interval whereas neutral and positive polarity for the second interval (Chakroborty et al., 2020).

In another study, authors presented a BERT model for sentimental analysis of negative posts in China (Wang et al., 2020). Rajput et al. presented a statistical analysis of twitter tweets during the pandemic. Authors applied word-frequency to comprehend the psychology and attitude of users (2020). The summary of related works concerning Covid-19 is present in Table 2. As per the literature, mentioned in Table 2, to classify the tweets basically SVM, LR, Naïve bayes and RF classifiers are used. Other different models are applied for different purposes. We have proposed a system framework which uses multinomial logistic regression for multiple classes. The use of multinomial logistic regression is three-fold. First, it is proven be an efficient algorithm to train the model. Second, the algorithm is performing well when dataset is linearly separable. Last, the algorithm is less inclined to

Table 1. Summary of Sentimental Analysis concerning different applications

Authors, Year	Emotions	Approach	Event	Media
Signorini et al. 2011	Public concern	Support Vector Regression Model	influenza H1N1 pandemic	Twitter
Tausczik et al. 2012	Anxiety	Linguistic Enquiry and word Count Model	H1N1 outbreak	Blogs, Newspaper Articles, Wikipedia
Lin & Margolin, 2014	Fear, Sympathy, solidarity	sentiment and time-series analyses	Boston bombings	Twitter
Soroka et al., 2015	Fear and anger	tailoring lexicons dictionary-based automation	-	News Stories
Towers et al., 2015	Fear	Contagion Model	Ebola	Twitter
Kharde & Sonawane. 2016	positive, negative or neutral	Naive Bayes, Max Entropy, and Support Vector Machine	-	Twitter
Lent et al., 2017	Fear	Vector Error Correction Model (VECM)	Ebola	Twitter
Effrosynidis et al., 2017	positive, negative or neutral	Linear SVC, Bernoulli Naïve Bayes, and Logistic Regression	-	Twitter
Krishnan et al., 2017	joy, sadness, anger, love, fear, and surprise	Naïve Bayes Classifier	Customer reviews on different products	Twitter
Rani & Singh, 2017	emotions	Support Vector Machine	Indian politicians	Twitter
Sulthana et al., 2018	positive, negative or neutral	Linear Regression	Predictive modelling	Twitter
Tyagi & Tripathi, 2019	positive, negative and neutral	K-Nearest Neighbor	-	Twitter

over-fitting. The present research study tries to find that how the social media tweets affect the public health-care system? Second, how the machine learning helps to analyse the emotions of human beings?

In relation to all the presented works, our study focusses on performance comparison of Covid-19 sentiment analysis using various machine learning algorithms.

METHODOLOGY

This section presents the methodology adopted for the current work. The proposed work operates into 4 phases. In the first phase, data collection and sentiment labelling are done. In the second phase, tweets pre-processing steps are performed to refine the data set that can be easily utilized for sentiment analysis. In the third phase, data splitting into training and testing sets is done. In this phase relevant features are also extracted. In the last phase, the model is trained using machine learning techniques to classify the tweets into positive, negative, and neutral. Figure 1. Illustrates the steps followed for performing sentiment analysis on Covid-19 data.

Data Collection

Sentiment140 dataset for twitter tweets on Covid-19 is used for the present study. The dataset is publicly available on the Kaggle. It contains 1.6 million tweets consisting of 0.8 million positive tweets and 0.8 million negative tweets. Table 3 presents the summary of data sets used. Authors of this data set considered tweets with positive emoticons as positive tweets and vice versa.

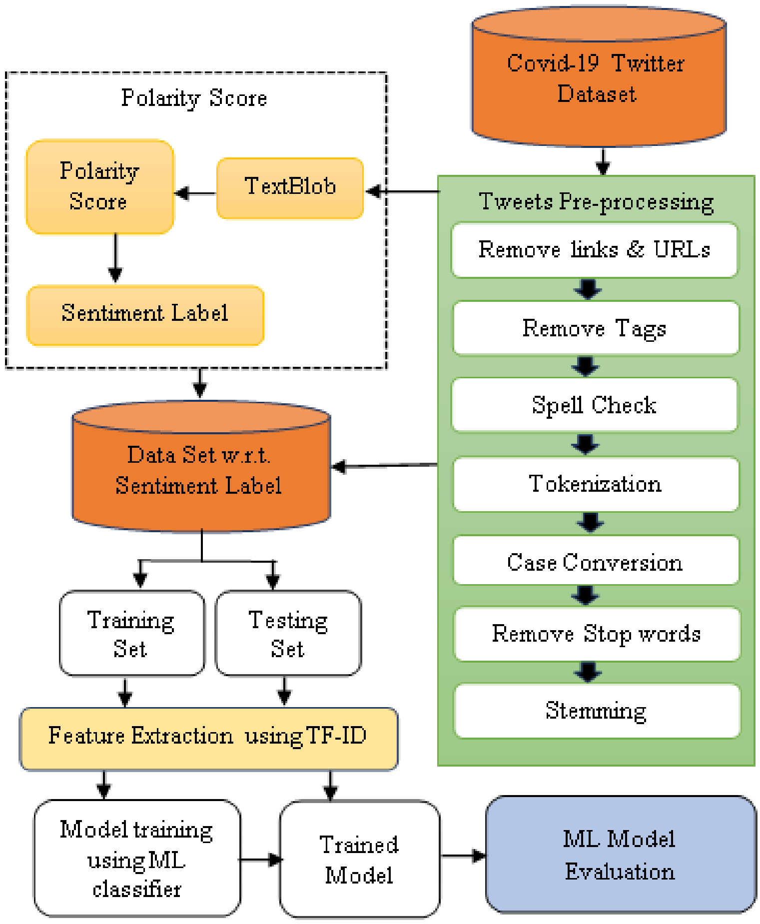
Table 2. Summary of Related work concerning Covid-19

Author, year	Purpose	Approach	Media
Samuel et al., 2020	Fear	Naïve Bayes, LR	Twitter
Jelodar et al., 2020	Detect meaningful topics	LSTM	Reddit
Imran et al., 2020	reaction of citizens from different cultures	LSTM	Twitter
Sanders et al., 2020	Mask	text summarization model using NLP	Twitter
Chakraborty et al., 2020	Effect of popularity	Deep Learning + Fuzzy rule base	Twitter
Wang et al., 2020	Discovering negative tweets	BERT model	Weibo
Zang et al., 2020	Emotional dictionary for Chinese text	BiLSTM + attention + CRF model	Micro blogs
Aslam et al., 2020	emotions evoked by news-headlines	Lexicon	Global news sources
Chintalapudi et al., 2021	Analyse Indian tweets	BERT model	Twitter
Rustam et al., 2021	Classification of tweets	LSTM	Twitter
Raheja & Asthana, 2021	Analyse positivity	polarity	Twitter
Kaur & Sharma, 2021	Classification of tweets	Naive Bayes, SVM, LR, RF Classifier	Twitter

Table 3. Data Set Summary

Data Set	Positive	negative	neutral	Total
Before using TextBlob (original data)	8,00,000	8,00,000	0	16,00,000
After using TextBlob	6,98,007	3,33,270	5,68,723	16,00,000

Figure 1. System Framework



Pre-Processing of Tweets

In the second phase, pre-processing was performed on tweets before performing the feature extraction as original tweets consist of misspell words, slang words, abbreviations, noise etc. These characteristics might hamper the performance of sentimental analysis. The pre-processing process followed is mentioned in Algorithm 1.

Re-Evaluation of Polarity and Splitting of Data Set

In the third phase, re-evaluation of polarity was performed as the original tweets data set has two assumptions: negative and positive. Only two assumptions were not sufficient for performing appropriate sentiment analysis. This work has used TextBlob to conquer the issue (Bose et al., 2020). It is a python library for performing natural language processing. It makes use of an "averaging" method for assessing a single word. This method works on the values of polarity to calculate polarity score for each word in a text. Finally, it returns a blended polarity for longer texts. In the present study, it returned the modified dataset which was more appropriate for performing the sentiment analysis. The changes in the dataset after applying TextBlob is shown in Table 3. The resultant data set was divided into training and testing sets with a ratio of 80:20.

Feature Extraction and Classification

In the fourth phase, features were extracted to make the data set suitable for defining the ML model. Data sets before applying feature extraction may contain different formats like text, sequence of symbols, and images. Feature extraction converts the data set into a format which can be directly used by ML models. In this work, authors used the frequency-inverse document (TF-IDF) technique for the feature extraction. TF-IDF is a statistical weighing numeric which is used to assess the importance of a word to a document in a dataset. Authors extracted features by assigning less weights to frequent used words and more weights to rare used words. Term frequency $\left(t_f\right)$ and inverse document frequency $\left(id_f\right)$ are computed using Equation (1) and Equation (2) respectively.

$$t_f\left(w^*, d_d\right)=log\left(1+f\left(w^*, d_d\right)\right) \tag{1}$$

Here, d_d is the given document from dataset and w^* is a given word in a document.

$$id_f\left(w^*, D_a\right)=\log\left(\frac{N_q}{f\left(w^*, D_a\right)}\right) \tag{2}$$

Here, N_q represents number of documents in a dataset and D_a represents collection of all documents.

After successfully extraction of features, data was classified by applying machine learning model. In the present study, authors applied the multinomial logistic regression model for the classification of tweets.

Multinomial Logistic Regression

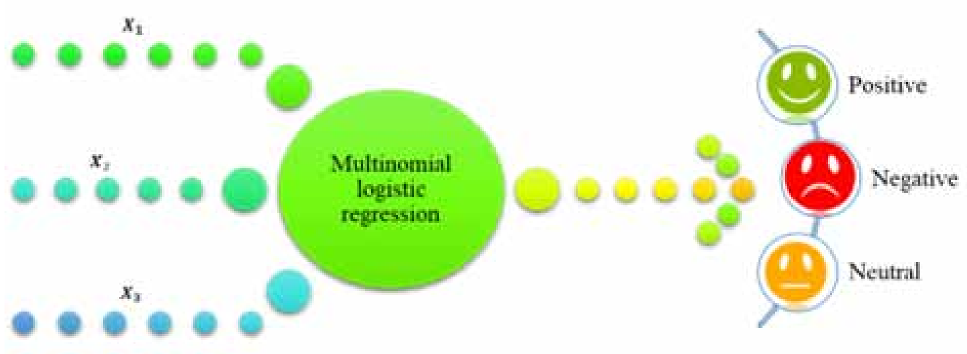
Sentiment analysis can be performed using NLP as well as machine learning techniques. From the literature, it is observed that the results of NLP techniques are less accurate as compared to machine learning algorithms. In the present study, machine learning is used for twitter sentiment analysis. Machine learning techniques allow to train the algorithm to be trained by certain training data. Output is prior known for the training data. Efficiency of trained models is tested for the new testing data. The present study introduces a new framework for the sentimental analysis of people during Covid-19 lockdown using multinomial logistic regression algorithm. To prove the efficacy of the proposed methodological framework, the work is compared with other machine learning algorithms like Naïve Bayes, decision tree and k-nearest neighbors.

Logistic regression is a statistical model which works on the logistic function for modelling a dependent variable. There are three different types of logistic regression namely binary, multinomial, and ordinal. Binary logistic regression supports two level categories whereas for supporting more than two values, the model is trained using multinomial logistic regression.

Multinomial Logistic regression is also known as SoftMax. It uses different weights for each word in each class which is utilized to assess the weights. Documents are represented as sparse vectors along with term frequencies (fig 2).

Let us consider for K class, K-1 models are formed for multinomial regression. It works as a set of independent binary regression. Suppose there are 3 classes of the dependent variable A, B and C. In case of two classes 1 vs 0 or (A vs B), we use to develop one logistic model that is, $Log\left(p/\left(1-p\right)\right)=a+b1*x1+b2*x2$. Here, $B_1,\ B_2 \dots B_n$ are the coefficient values and $x_1,\ x_2 \dots x_n$ are the independent variables. In this case if the probability >0.5 then class 1 or A else

Figure 2. Multinomial Logistic Regression for sentiment analysis



otherwise. However, multinomial logistic regression has more than two classes. Let's consider three as, -1 vs 0 vs 1 or (A vs B vs C). So, there is a need to select a reference class.

Now let's choose C as the reference class. Develop first model using Equation (3).

$$\log\left(\frac{p(A)}{p(C)}\right) = intercept_1 + b1*x1 + \ldots.. \tag{3}$$

Let us assign $\mathrm{RHS}_A = \mathrm{intercept}_1 + \mathrm{b1*x1} + \ldots$

Then $\frac{p(A)}{p(C)} = \exp(RHS_A)$ or $p(A) = p(B)*\exp(RHS_A)$ (4)

Similarly, we can build second model for $\log\left(\frac{p(B)}{p(C)}\right) = intercept_2 + b2*x1 + \ldots$

Let us assign $\mathrm{RHS}_B = \mathrm{intercept}_2 + \mathrm{b2*x1} + \ldots.$

Then $\frac{p(B)}{p(C)} = \exp(RHS_B)$ or $p(B) = p(C)*\exp(RHS_B)$ (5)

$$p(A) + p(B) + p(C) = 1 \tag{6}$$

Use the Equation (4) and Equation (5) in Equation (6). The resultant Equation (7) will be

$$p(C)*\exp(RHS_A) + p(C)*\exp(RHS_B) + p(C) = 1 \tag{7}$$

From equation (7), we can compute $p(C)$, $p(A)$ and $p(B)$.

$$p(C) = \frac{1}{1 + \exp(RHS_A) + \exp(RHS_B)}$$

$$p(A) = \frac{\left(\exp\left(RHS_A\right)\right)}{1 + \exp\left(RHS_A\right) + \exp\left(RHS_B\right)}$$

$$p(B) = \frac{\left(\exp\left(RHS_B\right)\right)}{1 + \exp\left(RHS_A\right) + \exp\left(RHS_B\right)}$$

Similarly, for k-class scenario $p(R) = \frac{\left(\exp\left(RHS_R\right)\right)}{1 + \exp\left(RHS_A\right) + \exp\left(RHS_B\right) + \ldots + \exp\left(RHS_{k-1}\right)}$

For the evaluation purpose, we have implemented three other machine learning models Naïve bayes, Decision tree and K-nearest neighbours. As per open literature, these algorithms are majorly used for sensitivity analysis.

Naïve Bayes algorithm depends on Bayes theorem and conditional probability. It is largely utilized in text grouping that incorporates a high-dimensional preparing dataset. Naïve Bayes Classifier is one of the simple and easiest classifiers that assists in making fast predictions. It makes predictions based on the likelihood of an object. This algorithm has been majorly used by researchers in applications like spam filtration, sentimental analysis, and ordering articles.

Decision Trees are supervised machine learning techniques which are usually used for classification as well as regression. The model runs for both categorical and continuous variables. The model predicts the value by learning through the data based on simple rules of decision and displayed in a hierarchical manner (Rose et al., 2020).

K-Nearest Neighbor (K-NN) It is another simplest supervised ML technique KNN algorithm works on the proximity. It considers an assumption that similar things have close proximity. For checking the closeness of proximity, the algorithm uses the concept of Euclidean distance (Rustam et al., 2021). K-NN calculation can be utilized for Regression just as for classification. However, generally it is utilized for classification problems. All these models can be evaluated based on different performance metrics. The present study is using the following:

Accuracy: It defines how much the predicted value is equal to the actual value and can be calculated as mentioned in Equation (8).

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions} \tag{8}$$

Precision: Precision defines the number of positive class predictions which belong to the positive class only. It is also called a positive predicted value. It can be computed as in Equation (9).

$$Precision = \frac{true\ positive}{true\ positive + false\ positive} \tag{9}$$

Recall: It specifies the quantity of positive class predictions made from all positive cases in the dataset. It can be calculated using the formula given in Equation (10).

$$Recall = \frac{true\ positive}{true\ positive + false\ negative} \tag{10}$$

F1 Score: It gives a single score after integrating both the precision and recall of the model as mentioned in Equation (11).

$$F1Score = \frac{2}{\left({}^{1}\!/_{Precision} + {}^{1}\!/_{Recall} \right)} \tag{11}$$

Support: It is the number of actual occurrences of the class in the specified dataset. Basically, it is the number of samples of the true response that lie in that class.

RESULTS AND DISCUSSION

In the present study, four machine learning algorithms (multinomial, Naïve bayes, Decision tree and K-nearest neighbours) are used to perform sentimental analysis of covid data taken from twitter. Each model is simulated using Python. Figure 3 illustrates the count of covid-19 twitter tweets based on polarity of sentiment analysis.

Table 4 presents the percentage of distribution of total number of covid-19 tweets among three different sentimental classes.

Through Table 4, it can be concluded that about 43.625% tweets were expressing positive sentiments and around 20.829% tweets were revealing negative sentiments. However, 35.545% tweets were conveying neutral sentiments.

Figure 3. Polarity Count for Covid-19 tweets

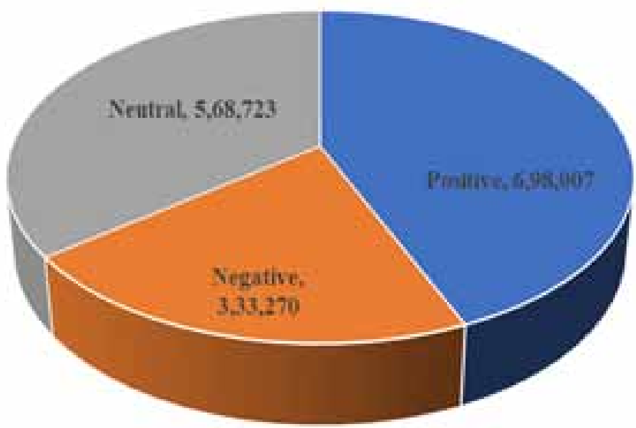


Table 4. Polarity of Covid-19 Twitter-tweets

Total Tweets=16,00,000	
Polarity	**Count**
Positive	6,98,007 (43.625%)
Negative	3,33,270 (20.829%)
Neutral	5,68,723 (35.545%)

The performance of each model is evaluated based on different performance metrics namely precision, recall, F1-Score and support as mentioned in section 4. However, Accuracy is considered as the primary parameter for performance evaluation. Table 5 demonstrates the validation results of the Multinomial logistics regression model. The model successfully attained the accuracy of 94%.

The result reveals that the precision value of “positive” tweets is highest (95%) among all three sentimental classes. It signifies the more correct categorization of “positive” tweets. The precision value of both the “neutral” and “negative” tweets are the same i.e., 94% which signifies that the framework equally performs the correct predictions for both classes. However, the recall of “neutral” tweets is highest (98%) and “negative” tweets is lowest (85%) among three classes. It signifies that the fraction of “neutral” tweets is correctly identified whereas it is lower in case of “negative” tweets. Similarly, F1-Score is highest for “neutral” tweets and lowest for “negative” tweets. It signifies that the maximum percent of positive predictions of neutral tweets are correctly done by the proposed framework.

The Naïve Bayes model achieved an accuracy of 71%. The results of Naïve Bayes algorithm are displayed in Table 6. The results conclude that the precision value of “positive” tweets is lowest (62%) whereas it was highest in case of multinomial logistic regression. The Naïve Bayes based model returns the highest precision value for “negative tweets”. Opposite to that it returns the highest recall value (97%) for the “positive tweets”. However, it is very low (35%) for “negative” tweets. F1-Score is also highest (76%) for “positive” tweets whereas lowest (52%) for “negative” tweets.

The Decision-tree based model achieved the accuracy of 91% better than Naïve bayes but less than multinomial logistic regression model. The results of the decision tree algorithm are displayed in Table 7. The results conclude that the precision value of “negative” tweets is lowest (86%). It returns the highest precision value for “neutral tweets”. Similarly, it returns the highest recall value (95%) for the “neutral” tweets. However, it is low (83%) for “negative” tweets and moderate (92%)

Table 5. Multinomial Logistic Regression Performance Metrics

	Precision	Recall	F1-Score	Support
Negative	0.92	0.85	0.89	66495
Neutral	0.92	0.98	0.95	113816
Positive	0.95	0.94	0.94	139689
Accuracy			0.94	320000
Macro-Average	0.93	0.92	0.93	320000
Weighted-Average	0.94	0.94	0.94	320000

Table 6. Naïve Bayes Performance Metrics

	Precision	Recall	F1-Score	Support
Negative	0.95	0.35	0.52	66495
Neutral	0.91	0.61	0.73	113816
Positive	0.62	0.97	0.76	139689
Accuracy			0.71	320000
Macro-Average	0.83	0.65	0.67	320000
Weighted-Average	0.79	0.71	0.70	320000

Table 7. Decision Tree Performance Metrics

	Precision	Recall	F1-Score	Support
Negative	0.86	0.83	0.84	66495
Neutral	0.93	0.95	0.94	113816
Positive	0.92	0.92	0.92	139689
Accuracy			0.91	320000
Macro-Average	0.90	0.90	0.90	320000
Weighted-Average	0.91	0.91	0.91	320000

for "positive" tweets. F1-Score is also highest (74%) for "neutral" tweets whereas lowest (84%) for "negative" tweets.

The K-Nearest neighbors-based model achieved the accuracy of only 48% which is lowest among all classifiers used in this study. The results of the K-Nearest neighbors algorithm are displayed in Table 8. The results conclude that the precision value of "neutral" tweets is lowest (41%) whereas highest precision value is for "positive" tweets. Unlikely, it returns the highest recall value (94%) for the "neutral" tweets. However, it is lowest (22%) for "negative" tweets. Maximum achieved value for F1-Score 57% for "neutral" tweets which itself shows poor results.

Table 8. K-Nearest Neighbors Performance Metrics

	Precision	Recall	F1-Score	Support
Negative	0.66	0.22	0.33	66495
Neutral	0.41	0.94	0.57	113816
Positive	0.83	0.23	0.36	139689
Accuracy			0.48	320000
Macro-Average	0.64	0.46	0.42	320000
Weighted-Average	0.65	0.48	0.43	320000

Figure 4. Accuracy of each ML model

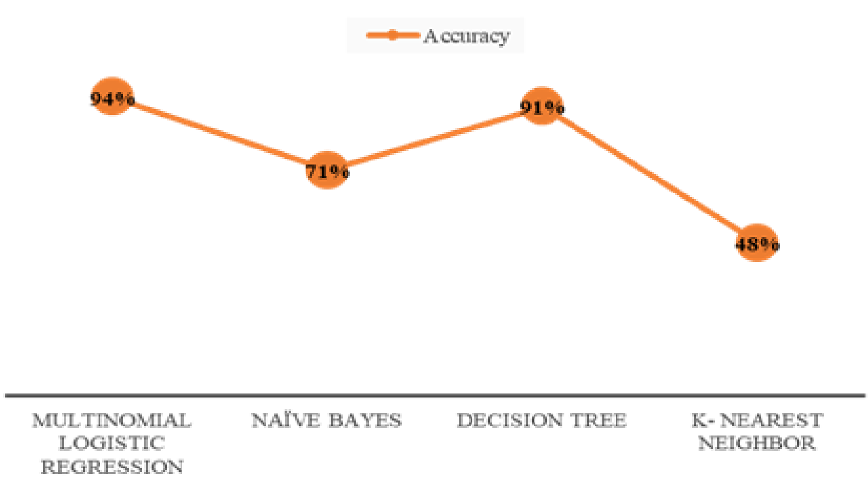


Figure 4 illustrates the overall prediction accuracy of each machine learning model considered for the classification. Multinomial logistic regression and decision-tree algorithms achieve much better accuracy over other two algorithms i.e., naïve bayes and k-nearest neighbors. K-nearest neighbors shows very poor accuracy as compared to the other three algorithms. However, multinomial logistic regression performs better as compared to all these algorithms.

Cohen's Kappa (k) statistics is also used to measure the inter-rater reliability. It is a quantitative-based reliability measure which is used by two raters to rate the same object. It checks how regularly the raters can agree. It can be computed as mentioned in Equation (13).

$$k = \frac{p_o - p_h}{1 - p_h} \tag{13}$$

Here, p_o and p_h are the relative observed agreement and hypothetical probability agreement respectively. The interpretation considered k is as mentioned in Table 9. The Cohen's kappa results are shown in fig. 5.

Training time complexity: Time complexity represents the measure of how fast an algorithm works on the input size. Suppose ' n ' is the number of training samples, ' d ' is the dimensions and ' k_1 ' is the closest neighbors. Table 10 shows the training time complexity of all the algorithms.

Multinomial Logistic Regression technique proved to be very decent with the low latency applications.

CONCLUSION AND FUTURE SCOPE

The present study analysis the twitter data on Covid-19 using multinomial logistic regression. The research performed the sentiment analysis on the tweets shared by the users to analyse the behaviour of the people during lockdown. The data is classified into three classes namely "positive", "negative" and "neutral". As per the precision results, 95% people have shared the positive tweets during lockdown which is highest among three classes. However, recall values for "neutral" tweets are highest. The model is evaluated in terms of accuracy, F-Score, and support as well. It is observed through experimental results that multinomial logistic regression is giving better accuracy of 94% as compared to other three machine learning algorithms namely Naïve bayes, decision tree and

Table 9. Cohen Kappa Score Interpretation

k	**Interpretation**
$k \le 0$	no-agreement
$0.01 \le k \le 0.20$	none-to-slight
$0.21 \le k \le 0.40$	Fair
$0.41 \le k \le 0.60$	moderate
$0.61 \le k \le 0.80$	substantial
$0.81 \le k \le 1.0$	perfect-agreement

Figure 5. Cohen Kappa Score for each ML model

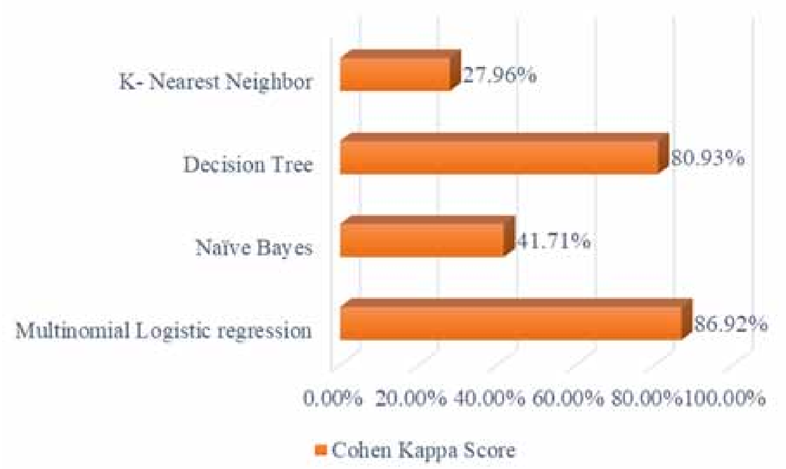


Table 10. Time complexity Analysis

ML Algorithm	Training time complexity
K-Nearest Neighbor	$O(k_1 nd)$
Decision Tree	$O(n * \log(n) * d)$
Naïve Bayes	$O(n * d)$
Multinomial Logistic regression	$O(nd)$

k-nearest neighbors. In the future work, we can improve the proposed framework by introducing the deep neural networks.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

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