Public Sentiment Analysis of Covid-19 Vaccination Drive in Pakistan

Ali Zaman[1], Saleem Iqbal[2,*], Saqib Majeed[1], Kashif Sattar[1], Ali Raza Bhangwar[3], Ghulam Mustafa[1],

[1]UIIT, PMAS-Arid Agriculture University Rawalpindi, Pakistan
[2]Department of Computer Science, Allama Iqbal Open University, Islamabad, Pakistan
[3]Department of Software Engineering, QUEST, Nawabshah, Pakistan
[*]Corresponding author: saleem.iqbal@aiou.edu.pk

Abstract

COVID-19 brought chaos to the globe for the last three years and so, throwing the everyday routine into disarray and triggering the collapse of the global economy while resulting in more than 2 million fatalities. To prevent a pandemic, the whole globe combined their efforts to find a cure and help develop a vaccine. Vaccinations commenced in 2020, and some countries began their vaccination campaigns at the end of the year, while others waited eagerly for the vaccinations to be approved. In the rapidly changing Covid-19 situation, social media is full of a broad variety of both good and bad tales. Though a number of people are interested in COVID vaccination, however, some are worried about the adverse effects and are still nervous over the dreadful ideas and after effects causing confusion. To assist the government in determining the public's reaction to the authorized COVID-19 vaccinations, it is crucial to ascertain the public's sentiments and views. In this study, the main objective is to check the response of the Pakistani community to vaccination against COVID-19. Up till now, statistical analysis is performed, sentiment analysis, and basic machine learning-based predictive analysis. Sentiment analysis is performed by using machine learning and deep learning algorithms. In our research, it is our finding that the neural network models CNN and LSTM models perform better than as compared to other Machine learning models like Naïve Bayes, Random Forest, and Logistic Regression. Although our study also concluded that between Naïve Bayes, Random Forest, and Logistic Regression. The Logistic Regression performs better on a larger dataset. With the results of Naïve Bayes at 63%, Random Forest at 63%, and Logistic Regression at 66%. While the accuracy of neural network models is CNN 81.1% and of LSTM is 81.3%. So, LSTM model is best to classify the tweets into their categories.

Keywords—COVID-19; Quality Assurance; Sentiment Analysis; Aspect Identification; Sentiment Classification.

1 Introduction

In December 2019 Wuhan, China reported the first COVID-19 case [1], and the virus has since spread to Europe and beyond. Respiratory disease caused by coronavirus is severe [2]. Over 2.17 million fatalities are attributable to this. A new epidemic of this illness began in March 2020. The number of valid instances reached 29.8 million and 4.3 million, respectively, on March 22, 2021. Globally, more than 3.99 million individuals have died because of COVID-19. Countries most severely affected by the disease concerning case numbers and death include the United States, Brazil, and India, as illustrated in Figure 1. And since July 23, 2021, it has infected over 192 million people [3], with approximately 4.1 million fatalities reported.

This worldwide pandemic caused major changes in the day-to-day activities of humans, including how academic work was performed, how people interacted, and how they conducted business or shopped. Although all of the exercises were disturbed by it, people having distinguished norms did not respond to the pandemic in a similar fashion. There is a cultural variation in Covid outbreaks, as several researchers have shown [4-6]. To research the attitudes of citizens from a variety of nations and cultures on the choices their governments made to deal with the Covid pandemic, data was collected from Twitter accounts from three different continents. Norway, Pakistan, India, Canada, Sweden, and the US make up this list. Sentiments indicated a strong link between India - Pakistan and Canada - USA. Even though Sweden and Norway are neighboring countries with many similar cultures,

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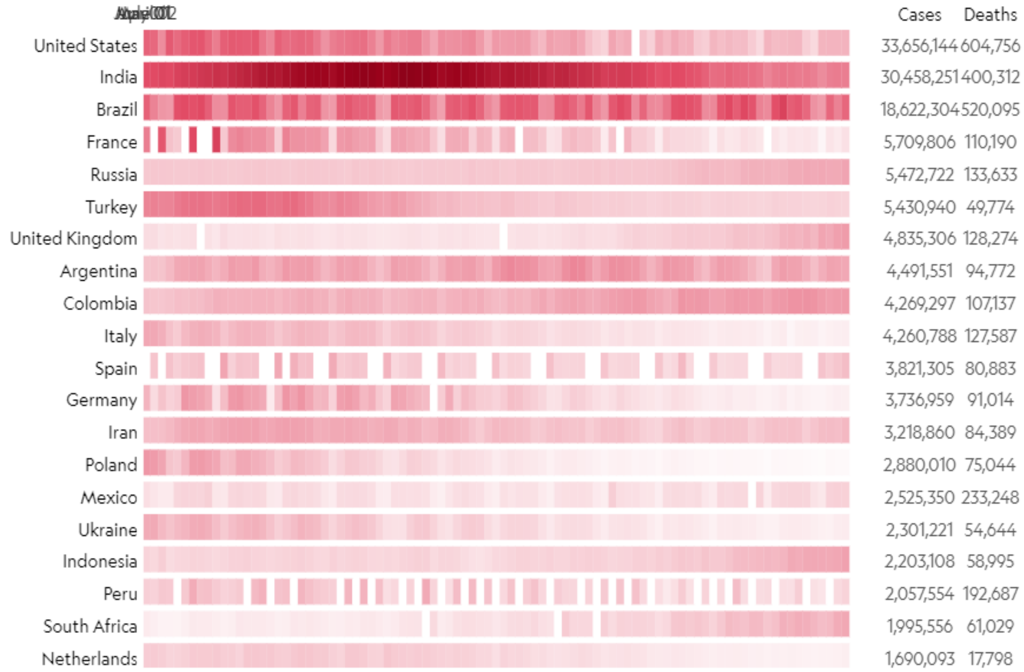

Fig. 1: Report of deaths and cases of COVID-19 of different countries

the tendency has shown the opposite. Many countries have started administering the COVID-19 vaccination to fight this almost insurmountable illness. African countries are trailing far behind in the fight against COVID-19, and Figure 2 shows the nations in which the Western nations are using the COVID-19 vaccination to protect themselves.

Four hundred sixty-eight million COVID-19 vaccines have been administered across 135 countries, according to Bloomberg's Vaccination Tracker as of June 24, 2021. 19.7% of the US population, or 128 million people, get at least one meal each day that is made using USA-grown produce. Over 4 million people in Canada have been immunized. In contrast to India, Pakistan has immunized 50 million people and has vaccinated just 325,000 people in its neighborhood. A total of 1.4 million persons in Sweden and 771,000 in Norway have been vaccinated. A smaller number of nations have also mentioned the potential adverse effects of the COVID-19 vaccine. Norwegian Medicine Agency accepted more than 1200 side effect complaints on February 18, 2021 [7]. Two districts in Sweden [8] discontinued their vaccination programs after February 14, 2021, after receiving complaints of adverse effects.

In March, after Denmark, which includes Norway and other Scandinavian and central European nations, AstraZeneca's vaccines were withdrawn from use in the population due to the blood clot-related fatalities occurring as a side effect. Social networking sites such as Facebook are places where people are eager to share personal experiences and social news and express their thoughts on what they hear. Many would reply and provide a variety of sentiments. It's in this paper's interest to push such a trend-forward since large events and demonstrations might then develop into riots, just as they did in the Arab Spring. Analysis of public sentiments on social media in a timely manner may help in preventing such an occurrence, and sentiment analysis is a technique that can efficiently be used to scan social media sentiment.

Deep neural networks, especially LSTM networks and their many variations, have shown their efficacy at extracting sentiment polarity from the text. The task's performance has been greatly improved because of word embedding schemes like FastText, GloVe, and BERT. Vaccinations are required for the development and progression of COVID-19 in order to prevent its spread and relieve the enormous clinical burden. Different pharmaceutical companies and institutions have managed to speed up the creation of COVID-19 vaccines. A few of the 260+ COVID-19 vaccines have been authorized. The new testing procedures [9] include some of the most state-of-the-art options. Pfizer is the first firm in the worldwide pharmaceutical industry to have its vaccine approved in different nations. Thus yet, the COVID-19 vaccine has only been given to a small percentage of 6% of the world's population, and its availability is still limited.

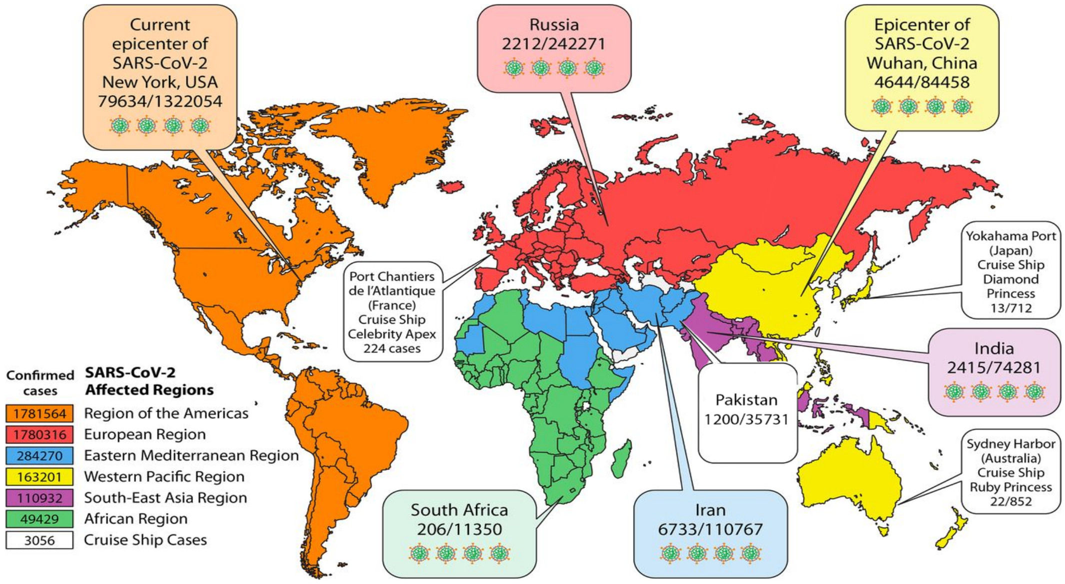

Fig. 2: The global population who got the COVID-19 vaccine (July 7, 2021)

2 Literature Review

One well-known application of NLP is Twitter sentiment analysis. The data analyzed and techniques used to do this task vary amongst researchers. Although there are many people who have already worked on a study on the COVID-19 vaccine examining the mood in tweets about the vaccine. It seeks to gauge the current pattern and an apparent change in vaccination rates in 6 nations, starting with the coronavirus. The results suggest that, although citizens of other nations have given almost identical responses to vaccination, they have been markedly different in their reactions to the coronavirus epidemic. For cultural emotion identification in the second coronavirus episode, this research utilized tweets from Twitter. The data was collected across different nations, with Pakistan and India being the two Asian countries. In comparison, the two North American countries, Sweden and Norway, represented the USA, Canada, and Europe. The search terms were "COVID19Pandemic," "lockdown," "StayHomeSaveLives," "Covid-19," "stayhome," "COV ID," "secondwave," "Coronavirus," "Covid19," "pandemic," and "vaccine." They were represented in the 801,692 tweets in the final data collection. Sentiments got normalized to $0 - 1$ by adding up the total number of tweets from a particular nation, equaling the number of tweets each day. Pearson's correlation values suggest that Pakistani and Indian people share good and negative sentiments far greater than people's feelings about vaccination drives in Canada and Norway, the United States, and Sweden. In comparison to Sweden, Norway's Pearson correlation is 70% for positive sentiments and more than 60% for negative ones. It reflects a greater consensus on vaccination sentiments among citizens of both nations, unlike their differing sentiments on the coronavirus epidemic. According to the findings, people's opinions of the vaccine and the second wave changed significantly after January 15, 2021. The coronavirus has caused a mix of favorable and negative public sentiments [11]. The primary goal of the research [10] is to comprehend people's perceptions, fears, and feelings that influence the achievement of the protection object by identifying the matters and opinions about corona vaccine-related debate over different platforms of social media and suggesting topic change and ideas over time. Modern systems have been examined in a study to address this issue. Over five datasets, 28 of the best academic and commercial systems were benchmarked. Overall, the accuracy rate was 61% across all domains and systems, which was not particularly great. This effort also included a thorough error analysis, which revealed that there are still many obstacles to overcome in this area. For instance, computers frequently misinterpret the user's purpose and are unable to understand sarcasm. [12] did a thorough analysis of various deep learning models for sentiment analysis. [13] Conducted extensive research on several deep learning models (RNN, CNN, DNN) and a large number of datasets relevant to the problem at hand. Before transferring the data to the models, TF-IDF was used to transform it. It was discovered that while there are numerous articles that study CNN, RNN, and LSTM separately on diverse datasets, there aren't any thorough comparative studies for them. A conventional deep neural network is trained using feed-forward neural networks [14]. Then, the multi-layered perceptron was contrasted with this. On the test set, DNN's accuracy was 75.03%, while the accuracy of MLP was 52.6%. To look into COVID-19-related discussions on Twitter and analyze people's attitudes toward the virus. This project used several ML techniques on data gathered from Twitter. The study looked at COVID-19 conversations using tweets written in English and originating solely in the United States from March 20 to April 19, 2020. Studies were also performed to analyze the networks of prominent themes, and the sentiments conveyed in the tweets. An additional geographic study was also performed. The total number of likes, responses, retweets, and mentions in tweets throughout the research period was 14,180,603, 863,411, 3,087,812, and 641,381, respectively. While 434,254 (48.2%) of the 434,254 tweets analyzed for the sentiment were positive, 187,042 (20.7%) neutral tweets, and 280,842 (31.1%) negative tweets, a total of 902,138 tweets were examined. The study's COVID-19-related tweets revealed five major themes: emotional support, public health, societal change, economics for business, and anxiety [15].

3 Methodology

In this study, positive, negative, and neutral tweets are used to train a sentiment analysis model. The procedure followed for this paper is illustrated in Figure 4. Imported tweets were pre-processed, represented, and then turned into features, and then passed into different models of sentiment analysis models.

3.1 Dataset Loading

The machine learning and deep learning models were trained using the dataset. It has 0.1 million tweets, each of which is classified with either a 0, denoting a negative sentiment, or a 4, denoting a positive sense. With 30,000 positive tweets, 30,000 negative tweets, and 30,000 neutral tweets, the set is properly balanced shown in Figure 3. These data are initially put into the system for additional preparation.

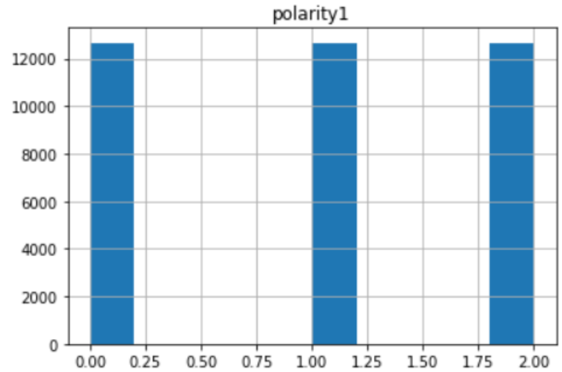

Fig. 3: Balanced Dataset

3.2 Dataset Preprocessing

The following procedures were used to pre-process tweets:

1) Removing Usernames: Tweets frequently contain the @ [username] notation for user names. Thus, user names are eliminated by eliminating terms that start with "@".
2) Removal of Links: Other posts or links are frequently included or referenced in tweets. As a result, it's essential to delete words that start with /http/https in order to erase linkages.
3) Elimination of Emoticons and Punctuation: Tweets are filled with emoticons and punctuation. The tweets had both punctuation and emojis removed.
4) Lowercase conversion: It is assumed that the case of the font has no affect on the meaning of the text and when more characters are added, the complexity of the data will rise. Every tweet is consequently changed to lowercase.
5) Elimination of Digits: Digits have been eliminated from all of the tweets because they have no impact on the text's emotion.
6) Eliminating Stop Words: Sentences are mostly carry stop words that don't add to the sentiment, such as pronouns (he/she, they, it/it's), nouns, verbs, adjectives, articles (the, an, a), and prepositions (after, far) [16]. These words were consequently removed from the tweets.
7) Stemming: Many words in phrases have prefixes or suffixes that can be eliminated according to grammatical rules because they have no impact on the sentiment. This work of breaking down words into their basic forms is carried out by stemming modules from programming languages [17]. On the tweets, stemming was applied [18].

3.3 Dataset Visualization

To better understand the dataset, Twitter visualization was done after data pre-processing. A Word Cloud was made in order to identify the words that were used the most frequently in the tweets. The Word Cloud of every tweet in the dataset is shown in Figure 5, and it can be seen that terms like go, not, and good are frequently used.

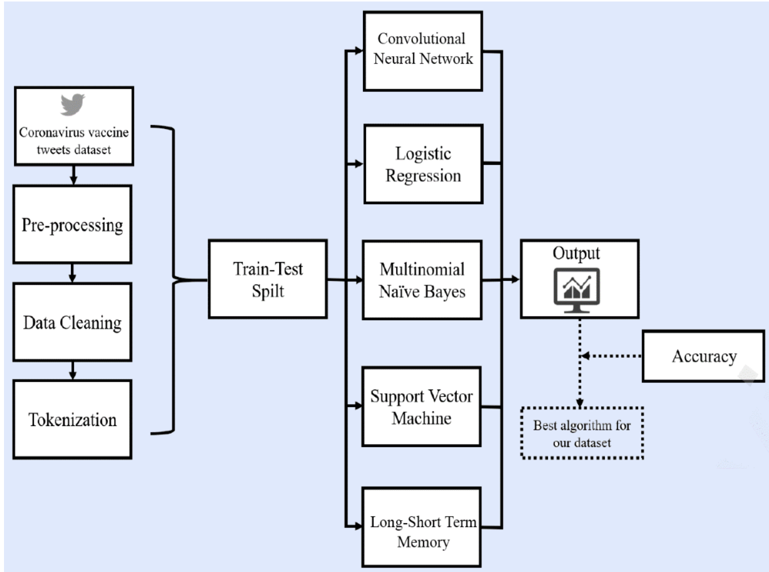

Fig. 4: Proposed methodology diagram

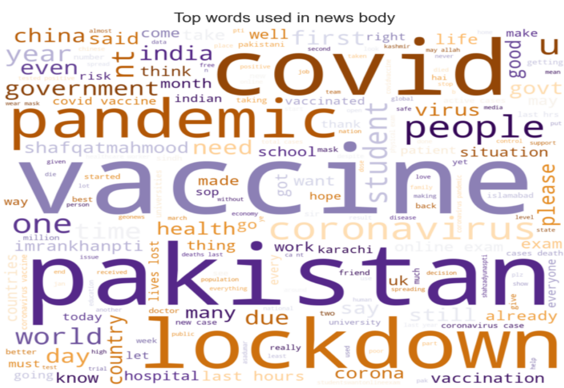

Fig. 5: Most frequent words in tweets

3.4 Feature Extraction

Following preprocessing and visualizing the tweets, feature extraction was performed. We applied the Word2Vec [19] method to turn the words in the tweets into vector representations because they contain words. To create a vector representation for each word, the Word2Vec model is trained on each word in the dataset. An embedding layer is then built using these representations, turning a sentence into an array of word vectors. A ratio of 80:20 was used to divide the dataset into train and test segments.

Evaluation Criteria

Accuracy, precision, recall, and the F1-score were the four benchmark performance measures we used.

$$Accuacy = \frac{TN + TP}{TN + FP + TP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1Score = \frac{Precision * Recall}{Precision + Recall}$$

TP is the true positive and was accurately predicted in the equations above. False positive and incorrect predictions are denoted by FP, true negative and accurate predictions are denoted by TN, and false negative and incorrect predictions are denoted by FN.

3.5 Model Training

3.5.1 Multinomial Naive Bayes

The Multinomial-NB Classifier is a probability-based supervised learning technique that specialises in classification of text. This approach adheres to the conditional probability multinomial distribution concept [20]. Although this approach uses multinomial distributions, text cases can be handled with it. One of the algorithms based on the Bayes theorem is naive Bayes. The Bayes theorem determines the probability $P(c|x)$, where x is the supplied instance that needs to be identified and c is the class of potential outcomes. The Naive Bayes assumption holds that all features are independent of one another [20].

$$P(A|B) = \frac{P(B|A) \times P(A)}{P(B)}$$

Where:

- $P(A|B)$: measure of frequency of occurrence of A and B combined (posterior likelihood)
- $P(B|A)$: measure of the frequency of B in A (likelihood)
- $P(A)$: measure of the general frequency with which A is seen to occur (prior probability)
- $P(B)$: measure of the general occurrence frequency of B (marginal likelihood).

Using data from the test set, the Nave Bayes Classifier's performance was evaluated. The Nave Bayes Classifier's precision, recall, f1 score, and accuracy are displayed in Figure 6.

3.5.2 Long Short-Term Memory

A type of memory that is an extension of recurrent neural networks is called Long Short-Term Memory (LSTM) [21]. It is commonly used in NLP to comprehend sentence context because it was created to learn long-term dependencies. A cell state through which information can pass and three gates via which information can be added to the cell state make up the LSTM as shown in Figure 7.

3.5.3 Random Forest

As a supervised learning algorithm, Random Forest is applied to regression and classification issues. The term "Random Forest" refers to a collection of trees, each of which is unique. It constructs many decision trees before merging them to produce an accurate and stable value that is mainly used for training and producing the class. Figure 8, displays the Random Forest Classifier's precision, recall, f1 score, and accuracy.

3.5.4 Logistic Regression (LR)

Text classification is one of the application of multinomial logistic regression, sometimes referred to as softmax regression, which is a supervised learning technique [22]. It is a regression model that applies LR to classification problems with more than two possible outcomes. Assume that there are k total classes and $m(x_i, y_i)$ pairs in the training dataset. Let $(w1, ..., wn)$ represent the set of n words that can appear in our texts using the bag-of-words. Figure 9 shows the benchmark of the Random Forest Classifier in terms of performance evaluation.

3.5.5 Convolutional Neural Networks (CNN)

A distinct type of multi-facet neural structure called a convolution neural network (CNN) consists of at least one convolution, pooling, and dropout layer, followed by at least one totally associated layer [23]. Convolutional and pooling layers provide input data to the fully associated layers for arrangement, removing significant element depictions from the input data in a verifiable manner. The amount of convolution channels determines how much information is stripped from the highlights. To eliminate comparable items in multiple spatial areas, the same convolution channel is drifted throughout the entire information set. Next, the Max Pool Layer is used to choose the key components from the CNN highlights. Therefore, it is taken care of to RNN model for order following focusing a few convolutional and max-pooling layers. Use softmax as an initiation function in the fully associated layer as a general rule at that time. Channels, steps, chunk size, padding, and enactment are CNN's boundaries. A detailed summary of the model is shown in Figure 10.

4 Results and Discussions

Deep learning models outperformed machine learning classifiers overall after running both ML and DL models. Deep learning classifiers included trained Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM), while ML classifiers included Multinomial Nave Bayes (NB), Random Forest (RF), and Logistic Regression (LR).

The reason is that CNN is better for image classification, while LSTM is better for text classification as compared to CNN because LSTM technique can extract the long-term relationship between the sequences of words, while the CNN technique uses convolutional layers and pooling layers to collect high-level feature extraction. Moreover, the graphical comparison of the evaluation of the models is shown in Figure 12. As seen in Table 1, LSTM eventually produced the best results in terms of all evaluation criteria. It produced an F1 score of 81.54% and an accuracy of 81.33%. This is due to the fact that LSTM can keep a text's context more effectively than other models because the information is transferred through it efficiently. Random Forest performed the worst overall, with an F-score of 62.30% and an accuracy of 62.50%. Following are the comparison results of all models which we applied to the dataset for classification.

From the above Table. 1, we can see that the Neural Network Models are best for classifying the text, and in comparison of CNN and the LSTM it gives the highest accuracy.

```
[[1764  570  161]
 [ 626 1531  405]
 [ 495  547 1499]]
              precision    recall  f1-score   support

           0       0.61      0.71      0.66      2495
           1       0.58      0.60      0.59      2562
           2       0.73      0.59      0.65      2541

    accuracy                           0.63      7598
   macro avg       0.64      0.63      0.63      7598
weighted avg       0.64      0.63      0.63      7598

Acuuracy of MultiNomial Naive Bayes Model is 0.6309555146091077
Precision: 0.638503
Recall: 0.630956
F1 score: 0.631188
```

Fig. 6: Results of Multinomial Naïve Bayes

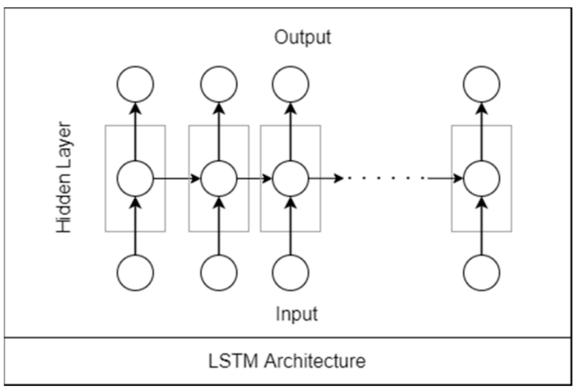

Fig. 7: Long Short-Term Memory

TABLE 1: Summary of sentiment analysis techniques

Models	Metrics			
	Accuracy	**Precision**	**Recall**	**F1-score**
RF	0.625	0.628	0.625	0.623
Multi-NB	0.631	0.639	0.631	0.631
LR	0.662	0.676	0.662	0.658
LSTM	0.813	0.814	0.813	0.813
CNN	0.811	0.811	0.811	0.810

5 Analysis of Public Opinion

After preprocessing, all tweets were also selected for the analysis of public opinion. The overall sentiments of the tweets are as under, In Pakistan, from 100% of tweets 31.4.7% have neutral sentiments 22.2% have negative sentiments and 46.4% are having positive sentiments. This shows that most discussion is positive, then negative, and then neutral, and in India from 100% of tweets, 28.3% have neutral sentiments 22.3% have negative sentiments and 49.4% are having positive sentiments. This shows that most discussion is positive, then negative, and then neutral. In this Figure 13, the chart also shows that in India there is a more positive discussion about vaccines as compared to Pakistan.

6 Conclusion

Sentiment analysis is context-focused message observation that obtains emotional data from the source material. In this research, the Twitter dataset is used and tweets were split into three categories neutral, positive, and negative. By examining the tweets, we have investigated the sentiments of people about COVID-19 vaccines in Pakistan. Most people are interested in the COVID-19 vaccine, whose tweets fall under the area of positivity. Sentiments and opinions will clarify the public response helping the healthcare authorities to analyze and recognize the attitude of the public and their distresses concerning the COVID-19 vaccine. The outcome of this research work is to help the government to understand public opinion and response toward COVID-19 vaccination. The health authorities will keep these things in reference they will boost vaccination drives and awareness programs according to the sentiments of the public. This research focused on detecting public sentiments, but it only took into account tweets written in English. In Pakistan, people typically use their native languages, such as Urdu, and Roman Urdu to communicate their feelings. In the future, the work can be expanded to include multilingual sentiment analysis for extracting emotions and feelings from social media posts about COVID-19 vaccines. While Facebook, Instagram, and other social media platforms should be taken into account to gain more

```
[[1853  470  172]
 [ 698 1359  505]
 [ 490  511 1540]]
              precision    recall  f1-score   support

           0       0.61      0.74      0.67      2495
           1       0.58      0.53      0.55      2562
           2       0.69      0.61      0.65      2541

    accuracy                           0.63      7598
   macro avg       0.63      0.63      0.62      7598
weighted avg       0.63      0.63      0.62      7598

Acuuracy of Random Forest Model is 0.6254277441431956
Precision: 0.628230
Recall: 0.625428
F1 score: 0.623277
```

Fig. 8: Results of Random Forest

```
[[2085  349   61]
 [ 813 1354  395]
 [ 551  399 1591]]
              precision    recall  f1-score   support

           0       0.60      0.84      0.70      2495
           1       0.64      0.53      0.58      2562
           2       0.78      0.63      0.69      2541

    accuracy                           0.66      7598
   macro avg       0.68      0.66      0.66      7598
weighted avg       0.68      0.66      0.66      7598

Acuuracy of Logistic Regression Model is 0.6620163200842327
Precision: 0.675645
Recall: 0.662016
F1 score: 0.658096
```

Fig. 9: Results of Random Forest

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_1 (Embedding)     (None, 80, 100)           5000000

 conv1d (Conv1D)             (None, 80, 64)            19264

 max_pooling1d (MaxPooling1D  (None, 40, 64)           0
 )

 flatten (Flatten)           (None, 2560)              0

 dense_1 (Dense)             (None, 3)                 7683

=================================================================
Total params: 5,026,947
Trainable params: 5,026,947
Non-trainable params: 0
```

Fig. 10: Summary of Random Forest

```
[[2192  185  162]
 [ 295 1891  364]
 [ 189  243 2077]]
              precision    recall  f1-score   support

     Neutral       0.82      0.86      0.84      2539
    Negative       0.82      0.74      0.78      2550
    Positive       0.80      0.83      0.81      2509

    accuracy                           0.81      7598
   macro avg       0.81      0.81      0.81      7598
weighted avg       0.81      0.81      0.81      7598

238/238 [==============================] - 1s 4ms/step
Acuuracy of CNN is 0.8107396960258484
Precision: 0.810890
Recall: 0.810740
F1 score: 0.809942
```

Fig. 11: CNN f1 score, precision, recall, and accuracy

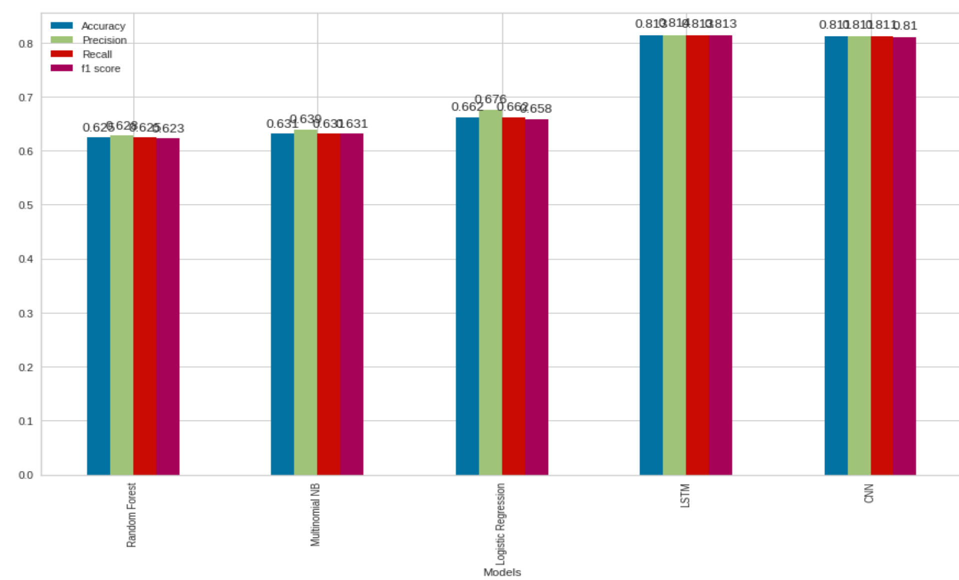

Fig. 12: Comparison of models

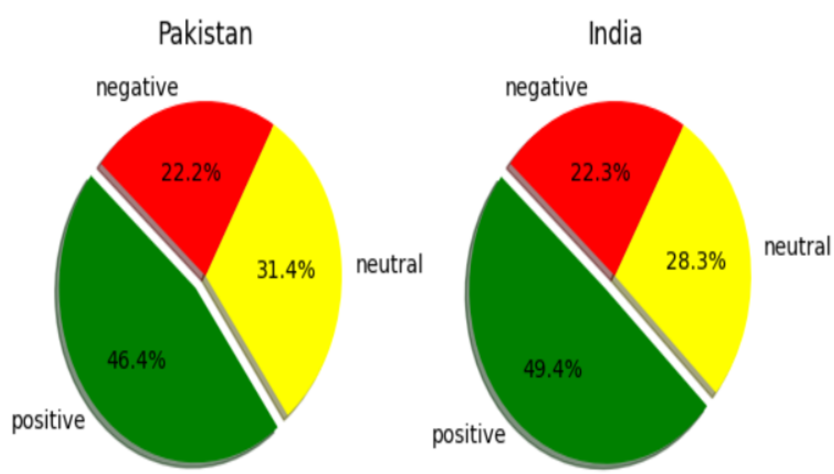

Fig. 13: Overall tweets sentiment distribution

insights regarding people's opinions related to COVID-19 and its vaccination process, we have limited our focus to tweets.

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