Covid-19 Vaccine Sentiment Analysis During Second Wave in India by Transfer Learning Using XLNet

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Abstract. The Covid-19 pandemic has created a world-wide crisis from the perspectives of health and economy. Vaccination is one of the prime means by which herd immunity could be developed. Social media platforms such as Twitter has played a major role in building public opinion as the vaccination drive got underway in several countries. In this paper, we present a tweet-based sentiment analysis of the two popularly administered vaccines in India Covishield and Covaxin during the second wave of the pandemic in India, from March 2021 to September 2021, which was attributed to the Delta mutant of the coronavirus. We use unlabeled Covid-19 vaccine-related tweets downloaded from a large-scale dataset from March 2021 to September 2021, and employ transfer learning for classifying the unlabeled tweets. The contributions of this paper are: - sentiment analysis of unlabeled vaccine-related tweets by training a transformer model on pre-trained XLNet (transformer) features derived from a labeled non-Covid Twitter dataset, a time-line of public sentiments for the two vaccines administered in India, and word clouds of high-frequency adjective unigrams after sentiment analysis, as evidence.

Keywords: Sentiment analysis · Covid-19 · Vaccine · Twitter · Unlabeled tweets · Covishield · Covaxin · XLNet · Transformer

1 Introduction

Covid-19 has spread world-wide for almost two years now, and has claimed more than 4.7 million lives. To counter the virus and develop herd immunity, vaccination drives are underway in all countries. Since their introduction, vaccines have received mixed reviews, which vary along with time as more awareness is spread among the masses [1]. Twitter is a social media platform used by 320 million people worldwide, and it has played a significant role in building public opinion about the Covid-19 vaccines [2]. Vaccine hesitancy and vaccine controversies need to be timely identified by the governments in order to take sufficient remedial actions, as asserted in several works [1, 3]. In India, the vaccination drive started in January 2021 after the first wave of the pandemic had abated. Covishield and Covaxin are the two popularly administered vaccines in India. An analysis of the tweets posted since March 2021 when the second

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wave started in India due to the Delta mutant of the coronavirus, till the abatement of the second wave in September 2021, would reveal the public sentiments for the two vaccines over time as the second wave progressed, and this is the task undertaken in this paper.

We particularly analyze unlabeled tweets since, as of now, it is difficult to get sentiment annotations for the Covid-19 related tweets since the pandemic situation is new and evolving. Some researchers have manually annotated tweets spread over a limited time span to train machine learning models [4–6]. However, training machine learning models with insufficient data may lead to overfitting or underfitting, rendering these models unfit to classify unseen test data. A list of Artificial Intelligence (AI) tools used for text mining from Covid-19 related social media posts is given in [7]. There are two main approaches for tackling unlabeled tweets. The first approach is to perform unsupervised sentiment analysis using sentiment lexicons that yield sentiment scores for each tweet, such as SentiWordNet, VADER, TextBlob or AFINN [8–11]. Sometimes, sentiment scores are used to identify phrase patterns that are associated with different sentiments [12, 13]. A majority of the researchers have adopted this approach for the sentiment analysis of Covid-19 tweets, examples being: - Yousefinaghani *et al.* (2021), Hu *et al.* (2021), Liu and Liu (2021), and Na *et al.* (2019) [2, 14–16] who used VADER, Marcec and Likic (2021) [17] who used AFINN, Sattar and Arifuzzaman (2021) [18] who used TextBlob and VADER. In [19], VADER, TextBlob and SentiWordNet were used to label news headlines into positive and negative sentiments. These annotations were then used to train a transformer model RoBERTa for sentiment classification. However, this method places a dependency on the efficacy of the three unsupervised techniques used for sentiment labeling. The second approach for handling unlabeled tweets is to train a model using a labeled dataset and apply it to classify the unlabeled tweets, a concept known as transfer learning [5, 20], which is the approach adopted in this paper. Recently, transfer learning was used successfully for sentiment classification of unlabeled social media posts related to the human papillomavirus [21]. One example of transfer learning related to Covid-19 text mining is the Covid-TWITTER-BERT model [22] which is a transformer-based model pre-trained on Covid-19 tweets, that can be fine-tuned for various text-based classification tasks. There are two main concerns while using a pre-trained model: - the selection of the labeled dataset and the choice of the classifier. In this paper, we use XLNet introduced by Yang *et al.* in 2019 [23], which is a recently introduced pre-trained transformer model, for supervised learning of the labeled *US Airlines* Twitter dataset which is a benchmark for tweet-based sentiment analysis. The trained model is then used to classify the unlabeled tweets related to the Covid-19 vaccines as positive, negative or neutral. The rest of this paper is organized as follows. Section 2 presents the methodology of the proposed sentiment analysis, Sect. 3 discusses the dataset, experimental setup and the results, and Sect. 4 summarizes the conclusions of the paper.

2 Methodology

This work is motivated by the need for testing the public sentiments related to the two vaccines popularly administered in India - Covishield and Covaxin, as the majority of the Indian population has already taken at least one dose of the two vaccines till date. Covishield is the Oxford Astrazeneca vaccine, while Covaxin is an Indian vaccine now approved by WHO. We obtained tweets in the duration of the second Covid-19 wave in India from March 2021 to September 2021, that are devoid of any sentiment annotations, from a large-scale Covid-19 Vaccine tweet dataset available online. The details of the dataset are discussed in Sect. 3. The tweets in the duration of the second wave in India are unannotated, which is an obstacle for supervised learning. In order to classify the unlabeled tweets into positive, negative and neutral sentiments, we perform transfer learning by pre-training a transformer model on XLNet features derived from the *US Airlines* tweet dataset [24] which is one of the benchmark datasets for tweet-based sentiment analysis. XLNet is an auto-regressive pretrained transformer model with multi-head self attention that has achieved high accuracies for text classification tasks [25, 26] as compared to the LSTM-based models with a single attention layer between the encoder and decoder [27]. XLNet is an extension of the transformer-XL model [28] introduced in 2019, that has outperformed the simple transformer for different classification and text generation tasks [29, 30]. XLNet introduced a modified language model training objective which learns distributions for all permutation of sequence tokens. The overall process flow for the proposed method is shown in Fig. 1.

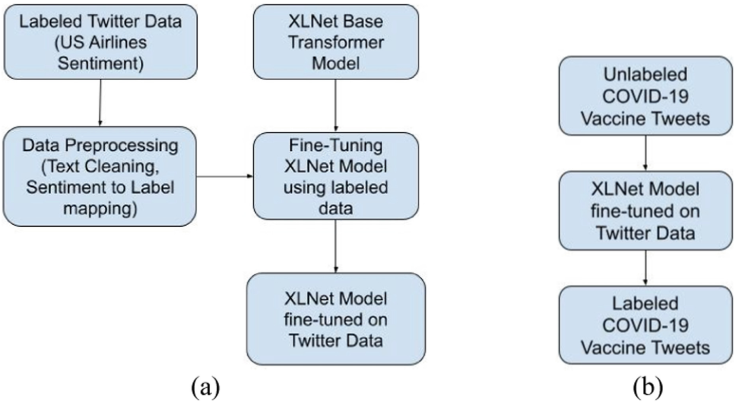


Fig. 1. Process flow: (a) Pre-training the XLNet model using *US Airlines* tweets (b) Classification of Covid-19 vaccine-related tweets using the pre-trained XLNet model.

The pre-training process is depicted in Fig. 1 (a) where the XLNet model is pre-trained on the *US Airlines* tweets that are sentiment annotated. A three-fold cross-validation is used for training the XLNet model on the *US Airline* tweets. In the second phase of our experiments, shown in Fig. 1 (b), the pre-trained XLNet model is used to classify the unlabeled Covid-19 vaccine-related tweets pertaining to the two vaccines – Covishield and Covaxin, that were popularly administered in India. The tweets so labeled are analyzed using time-line graphs to determine if the overall attitude towards vaccines has undergone a change, and if there is a boost in the general positivity of the social media users towards Covid-19 vaccines, during the course of the pandemic. We present the word clouds of high frequency adjective unigrams as evidence.

3 Experimentation and Results

3.1 Dataset Preparation

The Covid-19 vaccine dataset[1] contains tweets collected using tweepy in Python by Gabriel Preda. It contains tweets for seven different vaccines and has been updated till October 1st 2021 with a total of 197870 tweets. We separated out the tweets pertaining to either Covishield (also known as Astrazeneca) or Covaxin. We have not considered the tweets having a mention of both the vaccines, for the sake of simplicity. The total number of Covaxin tweets segregated by this procedure were 59,000 in number while Covishield tweets were 16,000 in number. The tweets were cleaned of URLs and links to websites, and all sentences were converted to lower case. Due to the absence of labels in Covid-19 vaccine dataset, a separate dataset labeled with sentiment annotations - the *US Airline* tweets dataset, was used to train a transformer model using XLNet pre-trained features, as explained in Sect. 2. This dataset is provided on Kaggle and is one of the most popular datasets for sentiment analysis of tweets. The trained model was used to predict sentiments for the unlabeled vaccine dataset, as explained in Sect. 2.

3.2 Results

The proposed method was implemented in Python 3.7 on a 2.8 GHz CPU. The methodology outlined in Sect. 2 was followed for training a transformer model using the labeled dataset, and further applying the trained model for classifying the unlabeled tweets pertaining to Covishield and Covaxin vaccines in the duration of March 2021 to September 2021. Table 1 presents the results of sentiment analysis for the *US Airlines* dataset using 80:20 train:test split with three-fold cross-validation, and a learning rate of 0.001, trained for 100 epochs. As observed, the XLNet model outperformed the unsupervised techniques of VADER and TextBlob, and supervised learning by Bi-LSTM and BERT models for sentiment analysis of the *US Airlines* tweets dataset, in terms of both accuracy and F1-score.

[1] https://www.kaggle.com/gpreda/all-covid19-vaccines-tweets.

Table 1. Sentiment analysis of US Airline tweets dataset using different classification frameworks.

Method	Accuracy (%)	F1-score
VADER	45.3	0.536
TextBlob	44.4	0.446
Bi-LSTM	81.1	0.801
BERT	84.2	0.843
XLNet	85.8	0.856

It was noted that the removal of stopwords and punctuations lowered the accuracy of our XLNet model. As observed from the confusion matrix plotted in Fig. 2 for the *US Airlines* tweets dataset, the XLNet model was able to correctly classify 85% of the positive tweets and 92% of the negative tweets. The model had some difficulty in distinguishing between the negative and neutral sentiments, but the precision and recall for both positive and negative tweets were high.

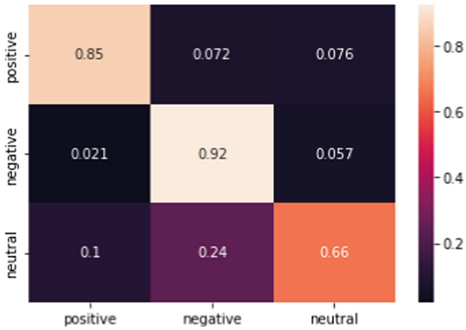
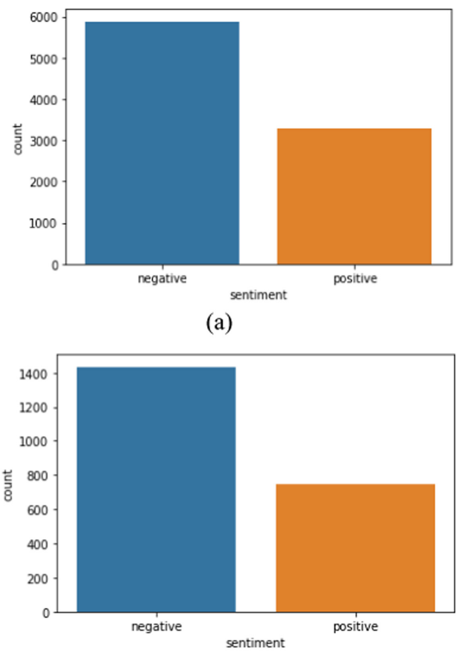


Fig. 2. Confusion matrix of the XLNet model trained on the *US Airlines* tweets dataset.

The transfer-learned XLNet model is now used for classifying the Covid-19 vaccine-related tweets into three classes: positive, negative and neutral. Figure 3 summarizes the sentiment classification results for the two vaccines in the form of bar charts. The neutral class is not shown since neutral tweets are mostly informational tweets and have no direct bearing on the understanding of the public sentiment. Our model classifies 11.14% of the Covaxin tweets as negative and 6.21% as positive; the rest are neutral tweets. Covishield tweets also follow a similar trend with 17.79% negative and 9.2% positive tweets. The positivity about Covishield only slightly exceeds that of Covaxin. The negative sentiment exceeds the positive sentiments for both vaccines due to apprehensions regarding the vaccination process during the course of the second wave of the pandemic in India. We next analyze time-line graphs to understand the changing public opinion in the duration of March 2021 to September 2021. Figure 4 shows the time-line graphs from March 2021 to May 2021 when the peak of the second wave was observed in India.

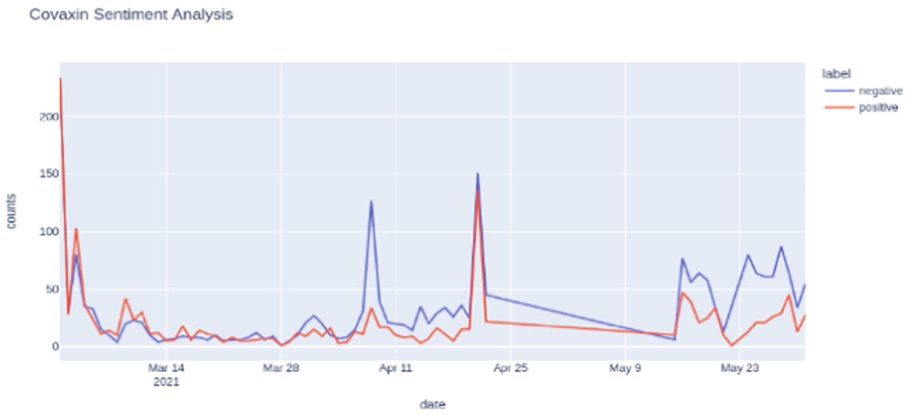


(a)

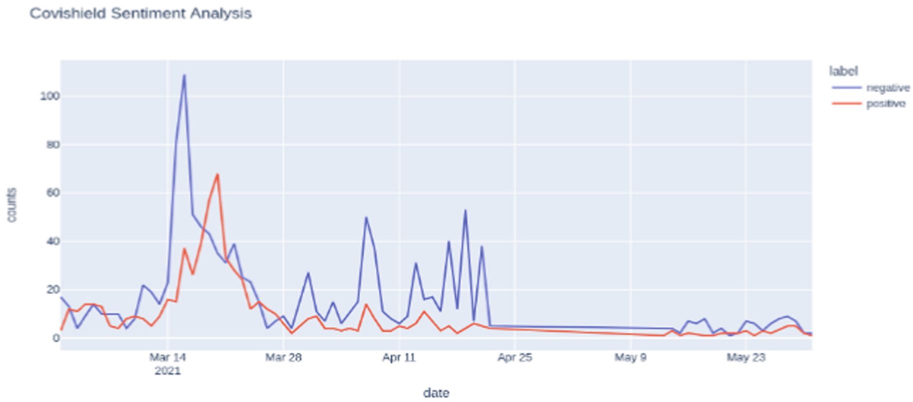
(b)

Fig. 3. Results of sentiment analysis of Covaxin and Covishield vaccine tweets by the proposed method.

Figure 5 shows the more recent graphs from June 2021 to September 2021. The graphs in Figs. 4 and 5 indicate that the overall negativity regarding both the vaccines (indicated by the blue line in both the graphs) reduces over time, with peaks observed in March, April and June. The positivity rate showed a spike in July 2021 possibly because of the reduction in the number of Covid-19 cases after the second wave in May 2021 subsided. However, the positivity is still low for both the vaccines, as observed from the graphs in Fig. 4.



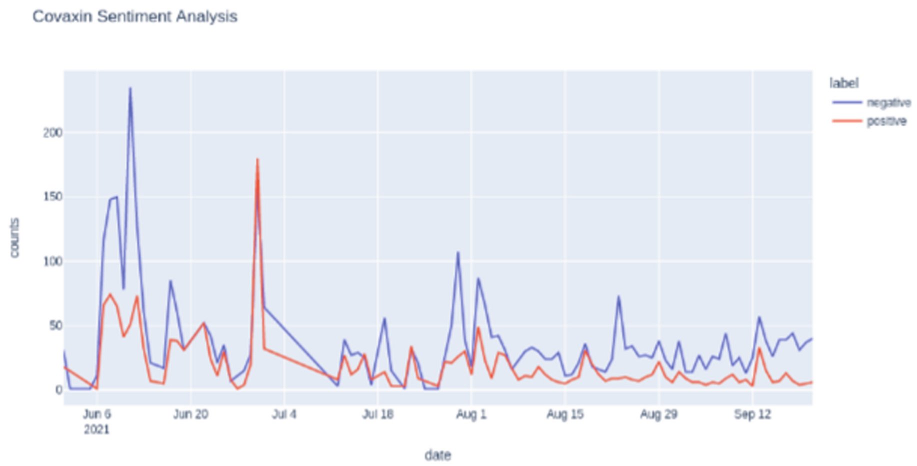
(a)



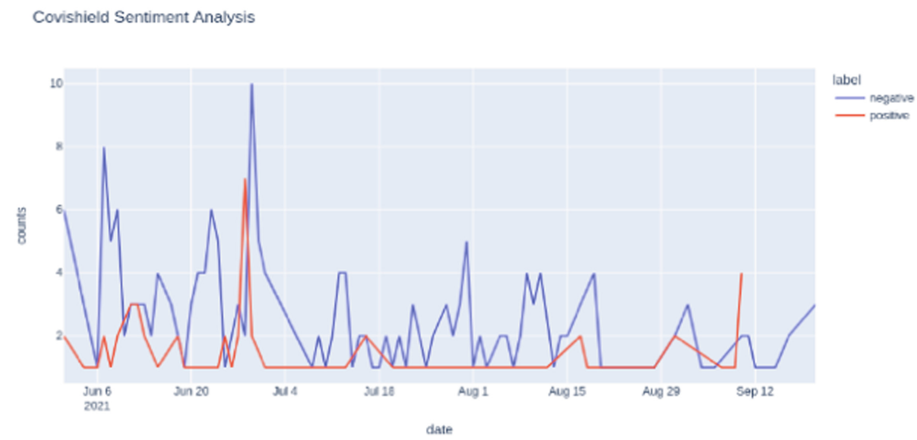
(b)

Fig. 4. Time-line graphs of public sentiments for (a) Covaxin and (b) Covishield vaccines from March 2021 to May 2021.

The term frequency in Natural Language Processing refers to the number of times a unigram occurs in a document. The set of highest frequency terms or unigrams indicates the class of the document [31]. We plot the word clouds of highest frequency adjective unigrams in Fig. 6 for the positive sentiments of Covaxin from the duration of March-May 2021, and also from June-September 2021. Likewise, we also plot the word clouds for the Covishield vaccine in Fig. 7.



(a)



(b)

Fig. 5. (From top to bottom) Time-line graphs of public sentiments for (a) Covaxin and (b) Covishield vaccines from June 2021 to September 2021.

In the initial phase, from March 2021 to May 2021, Covishield garnered a lot of positive comments as observed from the large number of adjectives in Fig. 7 (a) as compared to Covaxin in Fig. 6 (a). It is noteworthy that the frequency of positive words used for Covaxin has increased as compared to Covishield in the more recent times (June to September 2021) as observed from the higher frequency of the adjectives "*good*", "*great*" and "*effective*" in Fig. 6 (b). Another notable fact is the mention of 2nd dose found in both word clouds pertaining to the June to September 2021 time span, which indicates the increased positivity in public sentiments towards vaccinations over time. Further analysis shows that people have expressed their appreciation towards Covaxin with words such as "*indian*" and "*indigenous*" to showcase the fact that Covaxin was

(a) (b)

Fig. 6. Adjective word clouds of positive sentiments for Covaxin from (a) March 2021 to May 2021 (b) June 2021 to September 2021.

(a) (b)

Fig. 7. Adjective word clouds of positive sentiments for Covishield from (a) March 2021 to May 2021 (b) June 2021 to September 2021.

made in India. We show some negative tweets in Table 2, that showcase the advantage that XLNet has over the unsupervised techniques of VADER and TextBlob. The last tweet containing mixed reviews is labeled as negative by XLNet since it was unable to detect the smiley emoticon that was correctly recognized by VADER and TextBlob.

Table 2. Instances of negative sentiment analysis.

Tweets	XLNet	VADER/TextBlob
But I will not take it because it's not safe	Negative	Positive
#Covaxin is not finding international takers even when supplied free of cost	Negative	Positive
#Covaxin is no good as the 2^{nd} dose is reportedly not available	Negative	Positive
I am beginning to regret having #AstraZeneca vaccine. It's full of controversy	Negative	Positive
Arm hurts but head feels like it's been stomped… other than that I'm happy	Negative	Positive
Youngest cousin with his first vaccine shot:) #Covaxin Hyderabad, slots not easy	Negative	Positive

4 Conclusion

In this paper, supervised sentiment analysis of unlabeled tweets related to the two vaccines popularly administered in India: Covaxin and Covishield, was made possible by transfer learning using the latest transformer model XLNet, that is trained on a labeled non-Covid Twitter dataset. The transfer-learned model outperformed the unsupervised techniques of VADER and TextBlob that are currently used by most researchers for vaccine sentiment analysis, especially for the classification of the negative tweets. Analyzing the Covid-19 vaccine tweets dataset revealed that the negative tweets were more in case of both vaccines as compared to the positive tweets. The positive sentiments were found to have increased in the duration of June 2021 to September 2021 as the second wave gradually abated in India, as compared to the initial phase of March 2021 to May 2021 when the second wave attributed to the Delta variant peaked in India. The positive adjectives for the Indian-made domestic vaccine - Covaxin have increased as evident from the higher frequencies of the words – "*great*", "*best*", "*efficient*" and "*good*". Analyzing the tweets in two temporal phases for both the vaccines was beneficial as we were able to observe the public sentiments towards the two vaccines, and the vaccination process in general, as the second wave of the pandemic peaked and abated in India.

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