 doi:10.20944/preprints202204.0288.v1

A Deep Learning Approach for Public Sentiment Analysis in COVID-19 Pandemic

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***Abstract*—Sentiment analysis is a process of extracting opinions into the positive, negative, or neutral categories from a pool of text using Natural Language Processing (NLP). In the recent era, our society is swiftly moving towards virtual platforms by joining virtual communities. Social media such as Facebook, Twitter, WhatsApp, etc are playing a very vital role in developing virtual communities. A pandemic situation like COVID-19 accelerated people's involvement in social sites to express their concerns or views regarding crucial issues. Mining public sentiment from these social sites especially from Twitter will help various organizations to understand the people's thoughts about the COVID-19 pandemic and to take necessary steps as well. To analyze the public sentiment from COVID-19 tweets is the main objective of our study. We proposed a deep learning architecture based on Bidirectional Gated Recurrent Unit (BiGRU) to accomplish our objective. We developed two different corpora from unlabelled and labeled COVID-19 tweets and use the unlabelled corpus to build an improved labeled corpus. Our proposed architecture draws a better accuracy of 87% on the improved labeled corpus for mining public sentiment from COVID-19 tweets.**

***Index Terms*—Sentiment Analysis, Deep Learning, BiGRU, Word2Vec**

I. Introduction

A pandemic can be defined as an epidemic that spreads over international borders, frequently impacting individuals all over the world [3]. Sickness or disease is not a pandemic just because it is common worldwide or kills a lot of people; it has to be infectious as well. Throughout history, humankind had suffered from a large number of ferocious pandemics of diseases such as black death, HIV/AIDS, Asian flu, tuberculosis, cholera, Spanish flu, SARS, etc. causing deaths of millions of people across the globe. In recent years, the world is experiencing a new pandemic of a disease caused by a virus called COVID-19 which was appeared in late December 2019 in Wuhan, China. The whole world seemed to be collapsed at the initial phase of the COVID-19 virus when World Health Organization (WHO) detected and declared the infectious disease as a pandemic on March 11, 2020. Almost all of the countries across the world went to the lock-down situation to stop the spreading of the virus and took their safety measures. As a result, all the people needed to stay at home to keep themselves safe from this ferocious virus.

Social sites such as Facebook, Twitter, Youtube, WhatsApp, etc are already very famous throughout the mass people over the last decade. As these are popular media to express people's opinions, thoughts, reactions, and discussions, during the lock-down situation people became more active to share their views regarding the ongoing crisis. Most of the people tried to keep the positive intent about the pandemic, while on the contrary others were spreading fear as well as fake content, views, or tweets all over the social media. So, it becomes an utmost necessity to identify the sentiment of the mass people during the pandemic situation. This type of work with intelligent services can help all the organizations like financial, health, educational, transportation, restaurants, tourism as well as government to understand their people's views and to take necessary actions [1]. Researchers have been working hard to determine public sentiment in a pandemic situation. Sentiment analysis is a part of Natural Language Processing (NLP) which can be identified using various machine learning and deep learning approaches [4], [5]. In the context of computing, it can also be considered as a part of the broad area of data science with textual analytics [2].

Researchers frequently used COVID-19 tweets to perform the sentiment classification task about the pandemic situation [6]. This paper aims to mine public sentiment in a pandemic situation. To do so, firstly we developed two different types of

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corpora such as unlabelled and labeled corpus from the unlabelled and labeled COVID-19 tweets. Secondly, we trained our labeled corpus with the help of the unlabelled corpus to build an improved labeled corpus. Thirdly, we proposed a deep learning-based architecture using Bidirectional Gated Recurrent Unit (BiGRU) to perform sentiment analysis both from the labeled and improved labeled corpus. And, finally, we measured the accuracy, precision, recall, and f1-score of our proposed model.

The rest of the paper is organized as follows. Section II describes a brief overview of the related works for the sentiment analysis from COVID-19 tweets. In section III, the proposed methodology is explained whereas the results and discussion are analyzed in section IV. Finally, we conclude this paper in section V.

II. Related Works

Public sentiment analysis is a very important task especially in a situation like the COVID-19 pandemic to mine people's opinions, their demands, and their reactions. There are several research works regarding sentiment analysis in the pandemic situation that had already been conducted throughout the COVID-19 pandemic. Mainly different machine learning and deep learning techniques were used to perform sentiment analysis from COVID-19 tweets. To analyze COVID-19 related tweets for extracting sentiments, a clustering-based classification model named TClustVID was designed by (Md. Shahriare Satu et al. 2021) [7]. They applied their model on the COVID-19 Twitter dataset and got a higher accuracy than the state-of-the-art techniques of clustering criteria. An ensemble-based machine learning model can be used for sentiment classification from COVID-19 tweets. Three ensemble machine learning models such as voting classifier (VC), stacking classifier (SC), and bagging classifier (BC) were proposed in [8] for analyzing sentiment from 12k tweets which were gathered from the United Kingdom (UK). The authors in [8] got a better performance from stacking classifier (SC) with an f1-score of 83.5%, followed by the voting (VC) and bagging classifier (BC) with 83.3% and 83.2% f1-score respectively.

Naive Bayes (NB) and Logistic Regression (LR), two well-known machine learning approaches were applied in [9] for classifying coronavirus tweets of different lengths. The authors observed a strong accuracy of 91% only for classifying the shorter tweets using the Naive Bayes (NB) method, while on the contrary, they obtained an accuracy of 74% using the Logistic Regression (LR) method. However, both of these approaches showed comparatively less effective performance for the longer tweets classification [9]. Support Vector Machine (SVM), Random Forest (RF), Extra Tree Classifier, Gradient Boosting Machine, etc supervised machine learning approaches were executed with different feature techniques e.g. TF-IDF and bag-of-words (BoW) for US-based sentiment analysis [10]. Linear SVC, Perceptron, Passive Aggressive Classifier, and Ada Boost Classifier were tested with unigram, bigram, and trigram features for sentiment extraction from more than 72k COVID-19 related tweets in [11]. Valence Aware Dictionary for Sentiment Reasoning (VADER), a text sentiment analysis model was used by (A.J.Nair et al. 2021) for mining public opinion from COVID-19 tweets to help out public health organizations, as well as government officials [12]. In [4], [13]–[17], the authors had used Multinomial NB, Decision Tree (DT), Logistic Regression, Support Vector Machine (SVM), Random Forest Classifier with different features like weighted TF-IDF and n-gram to investigate sentiment analysis from the tweets related to COVID-19 pandemic to mine public anxiety.

Deep learning approaches [24] are also used heavily in the text classification domain over the few years successfully. To analyze the tweets regarding natural disasters like earthquakes and pandemics, Multi-Layer Perceptron (MLP) network was proposed by the authors in [18]. They measured the performance of the proposed network on the original COVID-19 dataset and obtained a classification accuracy of 83%. To point out the shortcomings of the proposed network and to explain the behavior, the authors used Local Interpretable Model-Agnostic Explanations (LIME) [18]. A deep learning classifier was developed in [19] to extract the sentiment from 226,668 tweets related to the pandemic situation and obtained an admissible classification accuracy of 81%. Deep Long Short-Term Memory(LSTM), a recurrent neural network along with FastText word embedding technique was applied in [20] to examine the responses of the citizens from the cross-cultural community to the novel coronavirus. The authors used the sentiment140 dataset for their experimental analysis and got a permissible accuracy of 82.4%. Artificial neural network (ANN) and LSTM techniques were executed to analyze the global sentiment about the coronavirus pandemic in [21]. For the LSTM network, the authors gained comparatively higher accuracy (84.5%) than ANN (76%).

Bidirectional Encoder Representations from Transformers (BERT) which is an efficient text classification model, were applied by the authors in [22] for multiclass classification of coronavirus tweets to determine the public opinion about the pandemic situation. The model showed an admissible performance by achieving 85% accuracy on the classification task. Though several research works were conducted to extract the people's thoughts and their opinion regarding the pandemic, most of these works did not use any pretrained corpus of COVID-19 tweets which may improve the performance of their proposed architecture. In this paper, we mainly aim to develop such a type of corpus and use that corpus to pretrain our experimental dataset and apply it to our proposed architecture for the sentiment analysis of the tweets in a pandemic situation. In the following section, we introduce the proposed methodology used in this research work.

III. Methodology

Fig. 1 depicts the methodology proposed in this paper. To carry out our experiment, we used two types of COVID-19 tweets dataset, one was unlabelled containing 7,59,848 COVID-19 tweets and the other one was labeled containing 36,623 COVID-19 tweets. Both of them were collected from

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the Kaggle platform and the first one was used only to build a corpus for COVID-19 tweets. The second one was used to conduct our research work. As from the Fig. 1 we can see that the first step of our proposed architecture is data cleansing for both of the datasets used in this paper. The data cleansing step includes performing tokenization, lower case conversion, punctuation marks removal, non-alphabetic characters removal, stopwords removal, and padding of the text data for both of the unlabelled and labeled datasets. To build an unlabelled corpus and a labeled corpus from the unlabelled and labeled datasets respectively is our next step. The following step is to develop an improved labeled corpus by training the labeled corpus with the help of the unlabelled corpus. Our proposed Bidirectional Gated Recurrent Unit (BiGRU) based deep learning approach is developed in the next step. We carried out two types of experiments, one was to classify the COVID-19 tweets into the positive or negative category from the labeled corpus and the second one was the same task as the first one except we used improved labeled corpus for the classification. To do so, labeled corpus and improved labeled corpus were split into train, validation, and test sets. Our BiGRU based deep learning architecture was trained and validated according to these train and validation sets and used for sentiment classification and prediction from COVID-19 tweets. Finally, the performance of our proposed model was measured in terms of precision, recall, f1-score, and accuracy. In the remaining part of the section, the details of our proposed methodology are described.

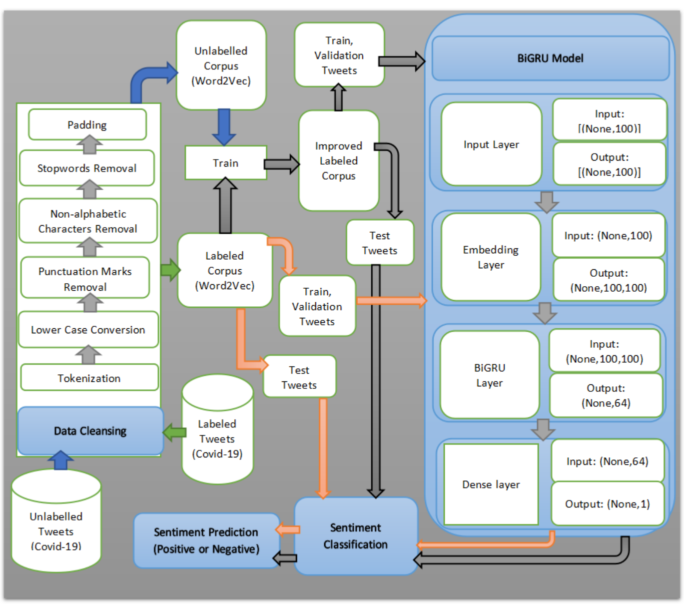

Fig. 1. Proposed methodology for sentiment analysis from COVID-19 tweets.

A. Data Cleansing

Data cleansing refers to the technique of removing unnecessary elements or noises from the data. In the case of Natural Language Processing (NLP), data cleansing means to preprocess text data by eliminating noises like stopwords, punctuation marks, emojis, non-alphabetic characters, etc. Preprocessing the text data is a mandatory task for any type of text classification or sentiment analysis problem. We performed the task of data cleansing for our datasets in the following way:

- Tokenization: Tokenization can be defined as a process of isolating the smaller units from a chunk of text called tokens. Tokens usually consist of characters, words, or subwords. For instance, if a tweet is like " stay home stay safe", we will get tokens like 'stay', 'home', 'stay', 'safe' after tokenization. We performed tokenization for each tweet of our unlabelled and labeled datasets.
- Lower Case Conversion: To preprocess the tweets, we converted all the tweets of our datasets into the lower case in order to maintain uniformity.
- Punctuation Marks Removal: For separating sentences or phrases, punctuation marks are used. Period(.), semi-colon(;), comma(,), dash (-), or question mark(?) etc are used as common punctuation marks. In the case of tweet preprocessing as punctuation marks do not have any significant impact, we removed them from our datasets.
- Non-alphabetic Characters Removal: Most of the tweets have a few number of non-alphabetic characters such as emoticons, emojis, or symbols etc. For cleansing tweets, these non-alphabetic characters must be removed because there will be no big deal on the tweets classification.
- Stopwords Removal: Stopwords are words that may have no meaning e.g. (conjunctions, prepositions, etc) and they are used frequently in the context of classification. They provide no essential information to determine the classification category of a tweet. For instance, stopwords like 'a', 'the', 'in', 'to' etc were removed from the token list of our datasets.
- Padding: As all of the tweets of our datasets did not have the same sentence length, we performed padding to make all the input of the same length.

B. Developing Corpus

In Natural Language Processing (NLP), corpus development is a mandatory task that may be defined as an organized set of machine-readable texts. At the end of the data cleansing step, we developed two individual corpora namely unlabelled and labeled corpus for our unlabelled and labeled datasets respectively. We used a well-known word embedding technique called Word2Vec to build our corpora. By using the word embedding technique, a word can be represented into a real-valued vector. The representation of words is done in such a way so that the same meaningful words are represented with almost look-alike word vectors. For instance, 'supermarket' and 'shop' will have closer word vectors. Word2Vec is such a type of word embedding technique to generate word vectors. It is a simple neural network with only one hidden layer. Word2Vec model uses the back-propagation technique during training for adjusting its weights and to reduce the loss function. The hidden weights are the word vectors that are generated after the completion of the training of the Word2Vec model.

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For developing unlabelled corpus we used vector_size = 100, window = 5, and min_count = 2 in our Word2Vec model. The same hyperparameters were also applied to generate the labeled corpus in the Word2Vec model. Once both of these were developed, we trained our labeled corpus with the help of the unlabelled corpus to build an improved labeled corpus. Later, we split both of the labeled and improved labeled corpus into train, validation, and test sets for training, validating, and testing our proposed model to classify COVID-19 tweets into the positive or negative category and for sentiment prediction. In the following subsection, we introduce our proposed architecture for sentiment analysis from COVID-19 tweets.

C. Proposed Model

Our proposed model is based on Bidirectional Gated Recurrent Unit (BiGRU) which is a Recurrent Neural Network (RNN) based architecture and an extension of the Gated Recurrent Unit (GRU) [24]. Fig. 2 shows the basic architecture of Bidirectional Gated Recurrent Unit (BiGRU), where, X_0,X_1....X_i represents the inputs and Y_0,Y_1....Y_i, (i= 0,1,2,..), represents the corresponding outputs from BiGRU layer respectively. Each layer of BiGRU architecture consists of sevreral GRUs. GRU can solve the vanishing or exploding gradients problem of traditional RNNs [23]. Unlike other RNN architectures, the internal cell state is not maintained by GRU. It has three types of gates which are update gate, reset gate, and current memory gate. Update gate determines how much of the previous information must be passed along into the future. On the other hand, the output gate determines how much previous information needs to be forgotten. The current memory gate is a sub-part of the reset gate, mainly responsible for reducing the effect of previous information onto the current information which is being processed for the future. The main goal of BiGRU is to examine a certain sequence from front to back and back to front. As a result, a context is constructed by the network for each character of the text depending on its pasts and its future. The BiGRU network appears to be identical to its unidirectional counterpart. The proposed architecture of this paper is shown in Fig. 3. The model consists of an input layer, followed by an embedding layer, a BiGRU layer, and a dense layer. We used ’sigmoid’ as an activation function at the dense layer and also used a dropout layer of 20% to avoid the overfitting problem. The total number of parameters of our model was 4,822,093, among them 25,793 were trainable and the rest were non-trainable parameters. Once the model was built, our next step was to compile and evaluate the model and to use that model for sentiment classification and prediction from the COVID-19 tweets as well. In the next section, we discuss the results and the evaluation of our model used for sentiment analysis from the COVID-19 tweets.

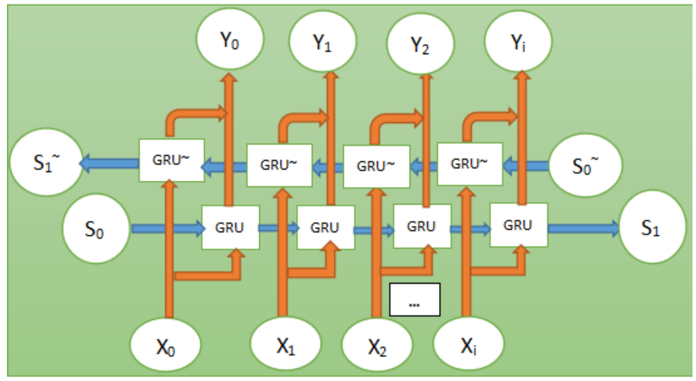

Fig. 2. BiGRU architecture.

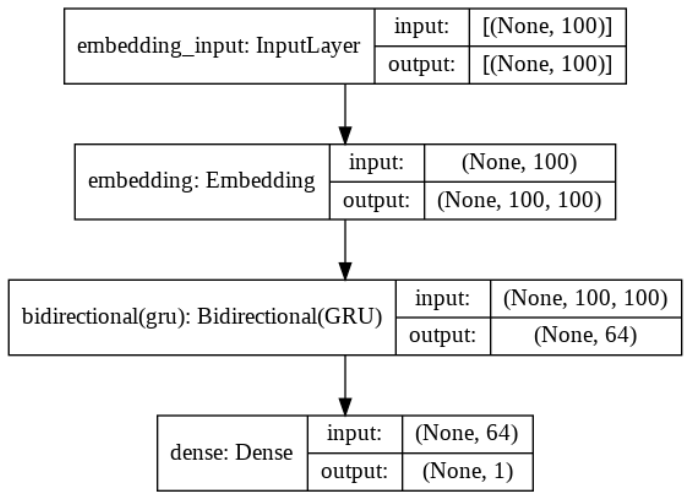

Fig. 3. Proposed BiGRU architecture.

IV. Results and Discussion

A. Dataset Description

To perform sentiment analysis from COVID-19 tweets, we used two types of datasets i.e unlabelled and labeled COVID-19 tweets from Kaggle as mentioned earlier. The labeled COVID-19 tweets dataset consists of 36,623 tweets among them, 19592 tweets were positive and 17,031 were negative and mainly used for sentiment classification. In the labeled dataset positive COVID-19 tweets were labeled as 1 whereas the negative ones were labeled as 0. As there is a slight imbalance between positive and negative tweets, to maintain the balance we executed the oversampling technique. The summary of the labeled dataset after data cleansing is described in table I in terms of the total number of words, mean of the words in a tweet, standard deviation, minimum and maximum number of words in a tweet.

B. Model Comilation and Evaluation

To compile our proposed model, we used ’adam’ as an optimizer, ’binary_crossentropy’ as a loss function, and ’accuracy’ as metrics. We executed our proposed model with a batch_size = 128 and for 50 epochs. Accuracy, precision, recall, and f1-score are measured to evaluate the model performance. Accuracy may be defined as the percentage of correct predictions for the test data. It can be measured by dividing the number

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TABLE I
COVID-19 LABELED TWEETS DATASET DESCRIPTION (NUMBER OF WORDS)

Total	Mean˜	Std	Min	25%	50%	75%	Max
44954	20.818793	7.100794	1	15	21	26	50

of correct predictions by the number of overall predictions.

$$Accuracy = \frac{CorrectPredictions}{OverallPredictions}$$

Precision can be defined as the fraction of true positives and the sum of true positives and false positives.

$$Precision = \frac{TruePositives}{TruePositives + FalsePositives}$$

Recall can be defined as the fraction of true positives and the sum of true positives and false negatives.

$$Recall = \frac{TruePositives}{TruePositives + FalseNegatives}$$

F1-score is a function of precision and recall.

$$F1 - score = 2 * \frac{Precision * Recall}{Precision + Recall}$$

We executed our proposed model in two types of scenarios. In the first case, we applied our model on the labeled corpus to classify COVID-19 tweets into the positive or negative category. In the second case, we applied our model on the improved labeled corpus to do the same task as the first one. Fig. 4 shows the performance of the model for the first case whereas Fig. 5 shows the performance of the model for the second case.

	precision	recall	f1-score	support
0.0	0.76	0.85	0.80	2642
1.0	0.83	0.73	0.78	2647
accuracy			0.79	5289
macro avg	0.80	0.79	0.79	5289
weighted avg	0.80	0.79	0.79	5289

Fig. 4. Performance of our proposed model on labeled corpus.

	precision	recall	f1-score	support
0.0	0.84	0.90	0.87	2638
1.0	0.90	0.83	0.86	2651
accuracy			0.87	5289
macro avg	0.87	0.87	0.87	5289
weighted avg	0.87	0.87	0.87	5289

Fig. 5. Performance of our proposed model on improved labeled corpus.

From Fig. 4, it can be seen that our model obtained an accuracy of 79% with f1-score of 78% and 80% for classifying both positive and negative tweets respectively. On the other hand, from Fig. 5, we can see that our model achieved an accuracy of 87% with f1-score of 86% and 87% for classifying both positive and negative tweets respectively. So it is clear that the performance of our proposed architecture on the improved labeled corpus is significantly higher than on the labeled corpus. The reason behind that is we developed an improved labeled corpus with the help of a pretrained corpus (unlabelled corpus). Because of that, we got more accurate word vectors and the model performed well in identifying the word sequences and eventually classifying them into the positive or negative category.

Fig. 6, 7 depict the train and validation accuracy graph of our proposed model on the labeled corpus and the improved labeled corpus in classifying the COVID-19 tweets respectively. The graphs explain for each epoch how the model achieved the training and validation accuracy.

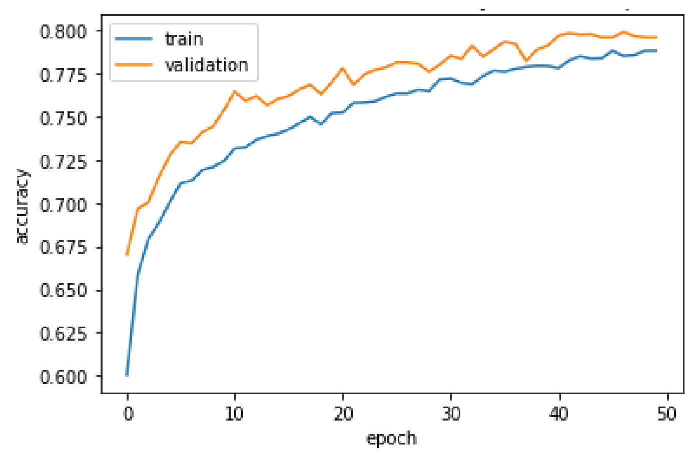

Fig. 6. Train and validation accuracy graph of proposed model (labeled corpus).

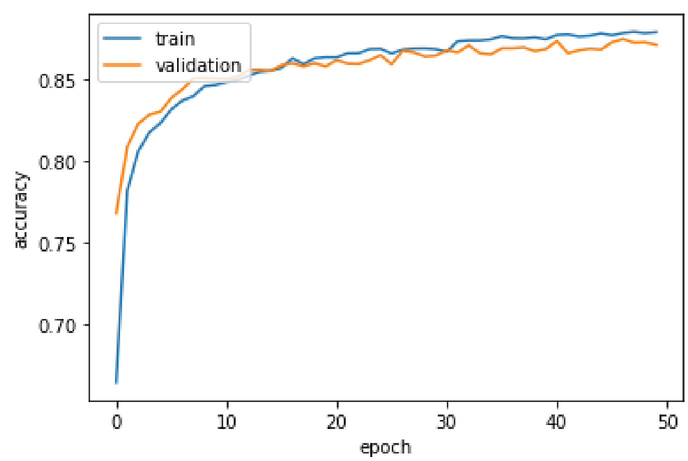

Fig. 7. Train and validation accuracy graph of proposed model (improved labeled corpus).

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V. Conclusion

Sentiment analysis can be an important tool to determine the views or opinions of mass people expressed on social sites regarding various crucial issues like the COVID-19 pandemic to identify the people's expression is positive or negative. In this paper, we mainly focused to mine public sentiment in coronavirus pandemic from COVID-19 tweets. We built an unlabelled and labeled corpus from unlabelled and labeled COVID-19 tweets and developed an improved corpus by training the labeled corpus using the unlabelled corpus. We measured the performance of our proposed deep learning approach (BiGRU based) on both the labeled and improved labeled corpus. Our proposed architecture shows better performance on improved labeled corpus by obtaining 87% accuracy, whereas on the labeled corpus an accuracy of 79%. Our future work will be to develop an efficient aspect-based multiclass sentiment classification model using a deep learning approach to mine public opinion.

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