A novel ensemble deep learning model for covid-19 Twitter sentiment analysis

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Abstract

Recent years have seen a rise in the significance of sentiment analysis as a direct result of the explosion in the amount of material available online. The practice of analyzing textual data created on social media sites such as Facebook and Twitter using a natural language processing approachis called sentiment analysis. Since the beginning of the COVID-19 pandemic, several postings, including videos and text messages, have been uploaded on the social media platform in order to provide real-time updates on the progression of the pandemic across the world's nations. The term refers to the practice of analyzing the word-based data created by social media platforms, which can be accessed, retrieved, and evaluated with relative ease. Most of the published research relating to COVID-19 issue theories were surveys of people's thoughts and ideas, and they explored the influence that the pandemic had on their life. This was because COVID-19 became prevalent after it was discovered. A very small number of researchers used a machine learning strategy for the task of analyzing the sentiment of social media. The rapid spread of the illness has resulted in a significant rise in the number of posts and comments made by users of social media, and these expressions of opinion cover a wide range of topics. The topic of sentiment analysis is discussed in this article, with the primary emphasis being placed on the categorization of the feelings sent by users in tweets originating from Twitter that are associated with COVID-19. Using deep learning techniques (CNN, LSTM, CNN + Bi-LSTM), as well as CNN + Bi-LSTM +CNN (CBC) a deep learning-based ensemble model, we were able to categorize the attitudes as positive, neutral, or negative. In comparison to the typical machine learning models, the Bi-LSTM technique has obtained more accuracy (0.98), when it comes to the categorization of Twitter sentiment. Based on the findings of the investigation as a whole, we are able to draw the conclusion that individuals have higher levels of optimism and confidence toward the recovery from the COVID-19 pandemic. A study of this kind will assist those responsible for making policies and decisions in meeting the requirements of the public in an acceptable manner.

Keywords: Deep learning, Twitter, covid-19, sentiment analysis, ensemble model.

1. Introduction

Since the coronavirus (COVID-19) disease first appeared in December 2019 in the Chinese city of Wuhan and quickly spreadto most countries around the world, many people have taken to social media to discuss the disease's origins, symptoms, prevention methods, and the efforts of developed nations and international research institutions to find a cure.Conspiracy theories regarding COVID-19 and its rapid propagation make up a large percentage of the daily news and social media material. Content shared on social media platforms shapes public belief and trends, which may or may not be based on proof but rather on anecdotes, conjectures, wishful thinking, or conspiracy fantasies.People use social media to learn about the disease, talk to others who have had similar experiences, and discuss the many issues surrounding the COVID-19 outbreak because there is no scientific indication from government sources or the World Health Society showing the true motives for the advent of the COVID-19 and its outburst.Now that the public is being evacuated, many individuals only talk about the Coronavirus online, on sites like Twitter. With more and more individuals depending on the service, the issue now is if and how we might use information gleaned from social media to help in the prevention, detection, and eventual containment of the COVID-19 pandemic. However, research on the public's thoughts and feelings regarding the COVID-19 outbreak is lacking. The purpose of this research is to monitor public opinion across many nations and over time in order to assess how people's reactions to the crisis have changed their expectations, perspectives, and actions.

The media also devotes much time and energy to covering this illness and reporting on how people are reacting to the guidance and directions offered by government establishments, such as adhering to the prohibition, remaining at home, isolating oneself socially, and eating healthily.Large social media platforms have rapidly adopted and widely encouragedseveral ways of information dissemination. More than 2.9 billion people worldwide regularly spend considerable amounts of time on social media. There are a variety of avenues open to investigation when analyzing Twitter data to learn more about public fears, worries, and perspectives on the COVID-19 epidemic. Using the gathered tweets, one approach combines topic modeling, natural language processing, machine learning, and sentiment investigation tools to determine the dominant themes and sentiments behind these patterns. There has been a lot of study in this area, with studies varying mostly in terms of their aims, the time span they cover, and the size of their datasets. For instance, Abraham et al. [6] investigated how people reacted to recommendations that they wear masks during the COVID-19 pandemic. Over a million mask-related tweets were gathered from January through April 2020 to evaluate for COVID-19. Each group of tweets was further separated into categories based on the sentiment analysis, with all of the tweets being grouped into 15 broad subject themes and 15 narrow topic themes. Summaries were then generated by using an abstractive text summarization model to each sub-cluster, which included integrating tweets that were connected in some way. Furthermore, weekly and worldwide divisiveness calculations were made, and lastly, linear regression of divisiveness with time was performed.

To track the blowout of false evidence on Twitter,Karishma Sharmaet al. [1] created a dashboard. This dashboard made it possible to monitor the coronavirus conversation taking place on social media and the accuracy of the data being shared in real-time. Furthermore, they developed a detection approach for identifying clickbait and other deceptive materials in the stream of information shared on Twitter. Merchant Raina M. etal.[2] looked at the significance of social media as a device for dealing with the ongoing widespread and growingfeatures of disaster planning and response. They stressed the essence of using social media to offerprecise information on several crucial issues during the prevalent ???, counting as when to examine, what to do with the findings, and where to obtain treatment. However, little research has really dealt with the issue of event detection by Doulamis Nikolaos D etel. [3], which is a significant issue in addition to the ones already highlighted. As an example, Farzindar Atefeh et al. [4] categorizedTwitter analysistechniques according to tasks, event categories, and the orientation of tweet content. Zafar Saeed etal.[5] conducted a similar literature evaluation, this time focusing on event recognition in Twitter data and categorizing it by event type, feature detection technique, and job. Zafar Saeed et al. Twitter event detection techniques were also categorised and emphasized their shortcomings. They also didn't provide many remedies to the problems with current approaches.

With its capacity for learning text sequences and discovering relationships between words or phrases, CNN + Bi - LSTM + CNN (CBC) model is used in our suggested method for sentiment analysis. Because the network is not picking up the proper volatility patterns in the data, it may also be utilized to improve the tweets' semantic data and the learning model's efficiency, leading to better overall performance on particular datasets. As a result, the following is the most important result of this research: It has been suggested that a CBC model be used to categorize tweets about COVID-19. A firefly optimization approach is presented for tuning the CBC model's hyperparameters in order to recover the model's overall presentation. Additionally, alternative state-of-the-art ensemble and machine learning-based approaches are compared to the proposed model's recital.

The remaining part of the paper is organized as follows. Some past research on the analysis of Twitter-related data is discussed in Section 2, along with the strengths and weaknesses of such research. Section 3 provides examples of the suggested technique. In Section 4, we describe the experimental setup and the dataset that wasutilized to test the suggested method. The findings of the suggested method are compared to those of other state-of-the-art models in Section 5. The study is wrapped up in Section 6 with some key recommendations for the future.

2. Related works

Due to the rising body of studies in this area, social network analysis of COVID-19 tweets using machine-learning approaches has become a prominent subfield of data mining. Using latent Dirichlet allocation (LDA), the authors in [11] were able to identify unigrams, bigrams, salient subjects, themes, and feelings from 4 million tweets posted about the COVID-19 pandemic between March 1 and April 21, 2020. Using a list of 25 trending hashtags, a dataset was generated from which important insights concerning health-related emergencies could be drawn. [12] is another research article that proposes using LDA for topic modeling. The authors examine the main emotion during a coronavirus epidemic and find that dread predominates.

To classify people's feelings about getting vaccinated against COVID-19, F.J.M. Shamrat et al. [7] used a supervised K-Nearest Neighbor (KNN) method. From 23 March 2020 to 15 July 2020, N. Chintalapudi et al. [8] collected tweets from Twitter users in India to conduct sentiment analysis. The information was first broken down into four groups representing anger, joy, fear, and sadness. After that, theyused a method called Bi-directional Encoder Representation from Transformer (BERT) to analyze the text. Experimental examination of Twitter data for sentiment related to the COVID-19 shutdown showed that the supplied model had superior prediction accuracy compared to other classification techniques including LSTM, SVM, and logistic regression. Using tweets from COVID-19, M.E. Basiri et al. [9] developed a unique deep-learning method for sentiment analysis. Eight nations, including Canada, England, Australia, Spain, Italy, Iran, China, and the United States, had their public opinion examined in this literature. At first, we gathered the tweets from eight users by searching for terms linked to coronaviruses. For sentiment analysis, a unique hybrid model was constructed that uses five deep classifiers: a Convolutional Neural Network (CNN), a Fast Text Model (FTM), a Naive Bayes Support Vector Machine (SVM), a Bi-Directional Gated Recurrent Network (Bi-GRU), and a Backwards Error Rate. The performance of the provided deep learning model was examined in this study using 1,000,000+ tweets from Stanford sentiment 140 Twitter dataset.

Regarding COVID-19 microblogging messages, the author in [10] developed a recurringdeep-learning approach for sentiment categorization. In particular, they suggested a strategy for identifying COVID-19-related themes. Our research is not drastically different from this one. They started with text analysis on Reddit and we started with data analysis on Twitter. Additionally, we studied tweets from 8 different nations while they just included global comments. Thirdly, we used deep learning with outdated machine learning techniquesto classify the tone of tweets, whereas they just utilized long short-term memory (LSTM) as a deep learning approach. After everything was said and done, their main emphasis was on topic extraction, whereas ours was on the withdrawal of Twitter users' attitudes around COVID-19[22-30].

A variety of machine learning methods have been put to the test by the authors of [15] on tweets mined from Twitter about the COVID-19 pandemic. Multiple machine learning classifiers, including Naive Bayes, support vector machine (SVM), decision tree, Logit Boost, and random forests, were used to categorize tweets as positive, negative, or neutral. When compared to other classifiers, the Logit Boost ensemble classifier's accuracy stands out. [16] used a Naive Bayes model to categorize English and Filipino tweets to analyze the public's opinion on the vaccination program against COVID-19 in the Philippines. During the emergence of COVID-19 instances in India, Chandra et al. [17] introduced a DL-based framework for sentiment study. Long short-term memory (LSTM) and bidirectional LSTM models with global vector (GloVe) were used for word depiction while building the language model. To further examine the differences between LSTM and Bi-directional long short-term memory (Bi-LSTM), the Bidirectional Encoder Representations from the Transformers model were implemented and the best model was used for sentiment analysis during the pandemicin India. The tweets on coronaviruses were evaluated using a sentiment analysis method developed by Sunitha et al. [18].Meanwhile, Samuel et al. [21] used ML methods to examine public opinion towards COVID-19 and looked at how tweet length affected classification accuracy.

In addition, the authors of [13,20] use deep neural networks to solve the issue of predicting aircraft demand time series. They tested a number of models and settled on the most effective one after doing a careful comparison. An LSTM-CNN-based system for classification is shown in a recent publication [14,19]. In particular, the suggested approach enhanced the classification problem by decreasing execution time by 30%-42%. This demonstrated the usefulness of the LSTM neural network and the significance of its contribution to certain tasks.

3. Proposed Methodology

An important goal of sentiment analysis is to deduce people's feelings about various elements of events and goods based on their online remarks. Sentiment analysis on Twitter has been used for a varied range of issues recently, with current events, invention reviews, film reviews, medicine reviews, and the categorization of Twitter streams during outbreaks. With the development of machine learning and deep learning methods, Twitter sentiment analysis has been a popular topic of study in recent years. The overall proposed methodology for analyzing the sentiments in the Twitter data is portrayed in figure 1.

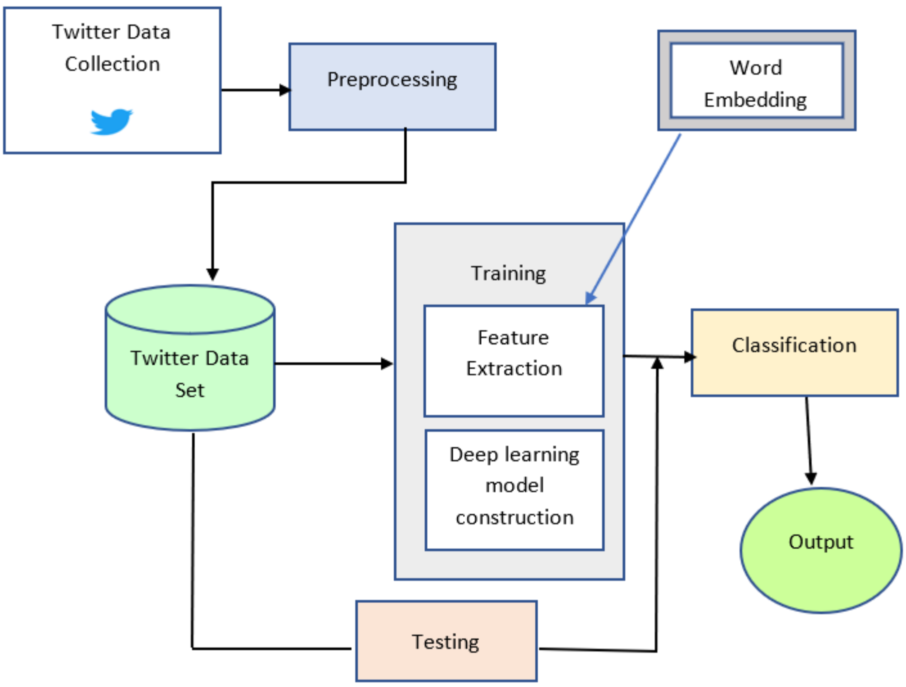

Figure.1. Overview of the proposed methodology

CBC Model

CNN is frequently used in feature engineering due to its ability to focus on what is most obviously present in the field of view. Time series analysis makes extensive use of a technique known as the BiLSTM, which is distinguished by the property of increasing in step with the progression of time. A CBC model that is based on CNN-BiLSTM-CNN has been constructed after taking into account the peculiarities of CNN and BiLSTM. Figure 2 presents the model structural diagram in its entirety. The fundamental structure consists of an input layer, a CNN layer (one-dimensional convolution layer, pooling layer), a BiLSTM layer (advanced LSTM layer, reverse LSTM layer), and a CNN layer (forward LSTM layer, reverse LSTM layer).

CNN begins with an input data matrix and proceeds to a data transformation, or "shaping," phase. After that, the largest pool block and two convolution blocks are applied continuously. Step 1 is intended to extract a certain amount of feature maps from the data, and each block convolves its input signal with an estimated kernel of step size between one and five. Next, the maximum pool layer is utilized to cut back on output. The goal of this layer is to reduce the complexity of the feature graph while keeping the same feature count. After a convolutional neural network (CNN) has been stretched, the Bi-LSTM is used with hidden neurons of size n to record the broad context.This information is merged from the forward LSTM and the backward LSTM layers of the LSTM model. After that, the BiLSTM will produce a vector with d dimensions and $2n$ dimensions, and the specifics may be stated using equations.

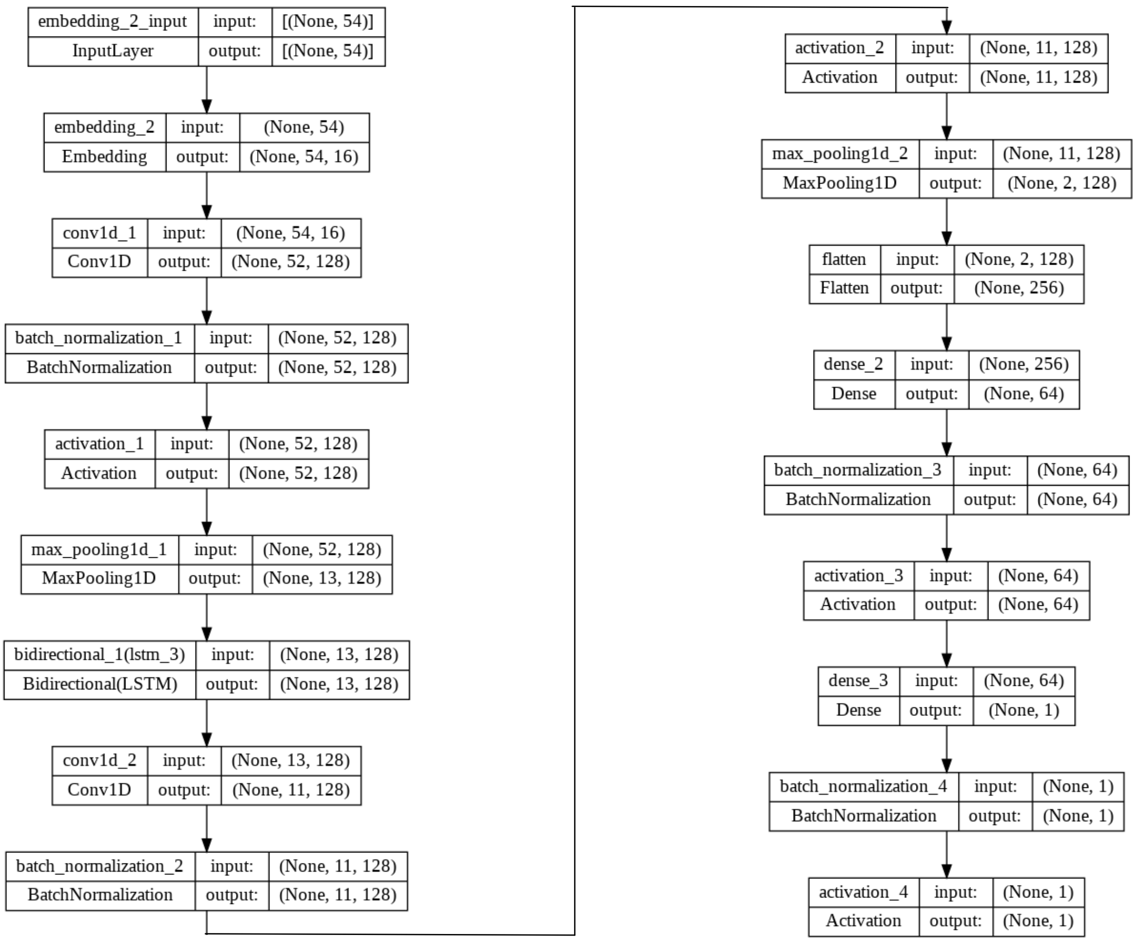

Figure 2. Proposed CBC model architecture

The following equations, where σrepresents the activation function Sigmoid, is an element-wise multiplication, and $w_{fg}, w_{ig}, w_{mg}, w_{og}$,are the weights and $b_{fg}, b_{ig}, b_{mg}, b_{og}$biases of the LSTM cell.

$$fg_t = \sigma(w_{fg}[hs_{t-1}, y_t] + b_{fg} \quad (1)$$

$fg_t$is the forget gate of Bi-LSTM which decides the information to be castoff.

$$ig_t = \sigma(w_{ig}[hs_{t-1}, y_t] + b_{ig} \quad (2)$$

$ig_t$is the input gate of Bi-LSTM which decides the information to be castoff.

$$\widetilde{mg_t} = tanh(w_{mg}[hs_{t-1}, y_t] + b_{mg} \quad (3)$$

$mg_t$is the memory cell gate of Bi-LSTM which decides the information to be castoff.

$$mg_t = fg_t * mg_{t-1} + ig_t * \widetilde{mg_t} \quad (4)$$

$mg_{t-1}$is the previous cell information. After going through the forget gate, mg_{t-1} makes the decision as to what information should be forgotten, $\widetilde{mg_t}$ makes the decision as to what information should be updated, and ultimately, mg_t is able to get the new cell information.

$$og_t = \sigma(w_{og}[hs_{t-1}, y_t] + b_{og}) \quad (5)$$

$$hs_t = og_t * \tanh(mg_t) \quad (6)$$

It is possible to retrieve the judgement state of the output via y_t and hs_t, and then the production of LSTM cell $hs_t - 1$ may be obtained by using the output gate together with the cell information. og_t is the output gate of the LSTM cell.

In conclusion, the output of the Bi-LSTM B algorithm may be expressed as

$$B = b_{1g} \oplus b_{2g} \dots\dots\dots \oplus b_{mg} \dots\dots \oplus b_{ig} \quad (7)$$

$$b_t = \left[hs_t^{fw}, hs_t^{bw}\right] \quad (8)$$

hs_t^{fw}represents the output of the Bi-LSTM in forward direction and hs_t^{bw} represents the output in the backward direction. The activation function used in the proposed models are calculated as,

$$\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \quad (9)$$

The sigmoid is calculated as

$$\mathrm{S}(x) = \frac{1}{1+e^{-x}} \quad (10)$$

The model's final decisions on attitudes are made in the fully-connected (FC) layer and the activation layer, following which the dispersion likelihood of the sentiment labels is generated. We use a three-layer architecture consisting of two FC layers and one softmax activation layer in this investigation.

$$R = softmax(\tanh\left(\tilde{k}W_1 + B_1\right) W_2 + B_2) \quad (11)$$

$\tilde{k}$ is the output of the previous top models and $W_1, W_2$are the weights and B_1, B_2 are the bias.

Loss function

In this particular piece of research, the cross-entropy function is used as the fundamental loss function, and the class weights, which include training class weights as well as assessment class weights, are intended to keep the training process in a state of equilibrium. In conclusion, a weighted adaptive loss function may be derived and well-defined as follows:

$$E = \Upsilon \times E^c + (1 - \Upsilon)E^{wc} \quad (12)$$

$$E^c = \frac{1}{k}\sum_{j=1}^{k} x_j log x_i^n \quad (13)$$

$$E^{wc} = \frac{1}{k}\sum_{j=1}^{k} w_j x_j log x_i^n \quad (14)$$

The equation (13) and (14) is submitted to equation (12). Thus, the equation (12) becomes,

$$E = \Upsilon \times \frac{1}{k}\sum_{j=1}^{k} x_j log x_i^n + (1 - \Upsilon)\frac{1}{k}\sum_{j=1}^{k} w_j x_j log x_i^n \quad (15)$$

$$E = -\frac{1}{k}\sum_{j=1}^{k}(\Upsilon + (1-\Upsilon) \times w_j)x_j log x_i^n \quad (16)$$

$E^c$and E^{wc} represents the cross entropy and the weighted cross entropy loss functions. The number of classes for the output classification is marked as k.

After that, the output of two pooling layers is placed into a full connection layer, and the output features of the final layer are aggregated by the full connection layer to generate a global feature that is used for text emotional categorization. At long last, these characteristics will be sent into the bottommost layer, which will consist of five neurons, and the probability vectors will be produced by the application of soft max.

Hyperparameter Tuning

In statistical parlance, the process of hyperparameter tuning involves taking a snapshot of the present performance of a model and comparing this snapshot with others that have been taken in the past. The hyperparameters of a deep learning algorithm must be set before a model can begin training. Fine-tuning the model's hyperparameters will enhance its results on a validation set. In machine learning, a hyperparameter is a parameter whose value is set in advance of the actual learning process. On the other hand, the parameters of the model are learned from the data. The parameters of a model are its weights and coefficients, which are calculated by an algorithm from the available data. Our suggested model's optimised hyperparameters are listed in table 1.

Table 1. Hyperparameter Tuning

Hyperparameter	Value
Activation Function (CNN)	ReLu, Softmax
Activation Function (Bi-LSTM)	Sigmoid, tanh
Dropout	0.5 and 0.3
Learning Rate	0.001, 0.00001,0.0001,
Batch Size	16, 32, 64
Training Data	80%
Test Data	20%
Optimizer	Adam
Epoch	20
Dense Layer	3

4. Experiment

The suggested CBC model has been fully described in Section 3. In this part, we develop the model and evaluate its performance experimentally to prove its superiority. The tests look at many aspects of the model's performance, including how it compares to other models, how well it can be visualised, and how prone it is to making mistakes. Each method is written in the programming language Python and uses the open-source learning package Keras, which is based on TensorFlow. All the research is conducted on a Windows 10 machine with a 2.6 GHz Intel i7-4700H CPU, 12 GB of RAM, and the latest version of the Windows operating system.

Dataset

According to the findings of the Covid study, Twitter's widespread usage may be attributed to the platform's users' high level of engagement. Because of the massive volume of data that is created on Twitter, it may be quite time-consuming to promptly reply to users' tweets. When analysing tweets on social media platforms, sentiment analysis may be of great use.

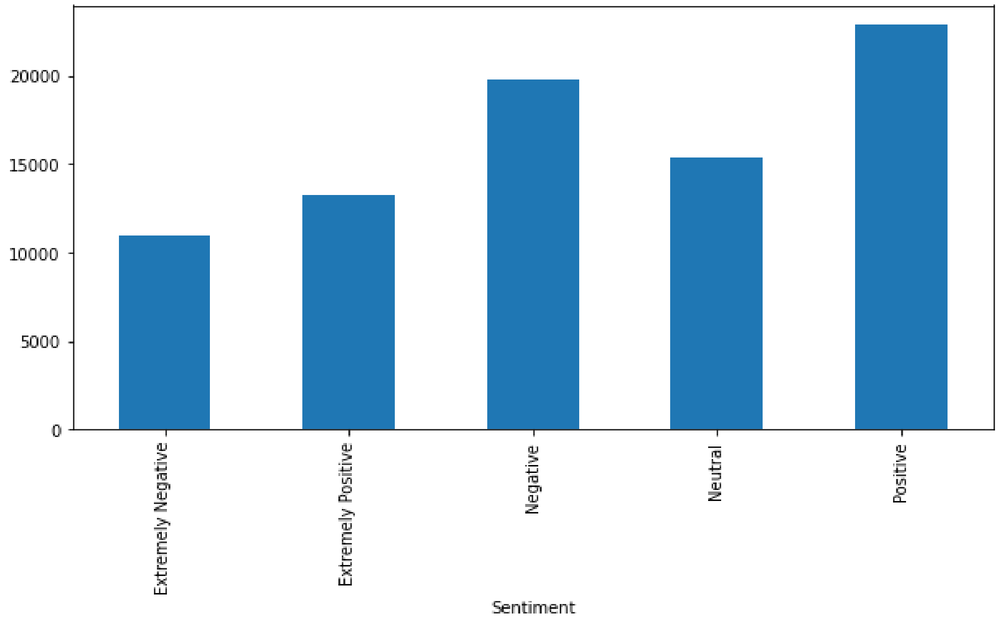

Figure 3. Twitter data collection

Monitoring the emotions expressed in tweets about Covid-19 is possible with the use of this technology. The first thing that has to be done in order to do the sentiment analysis on the tweets from social media platforms for Covid-19 is to carry out the data collection. Tweepy is the application programming interface (API) for Twitter that was used in this research to gather the tweets relating to Covid-19. In order to make use of this API, you will need to complete a number of procedures, such as creating an account, downloading and installing Tweepy, carrying out the quick test, inspecting JSON tweets, parsing data, identifying data, and collecting data.This competition is a multi-label text classification challenge, and it focuses on analysing the sentiment of Tweets that are relevant to the Covid-19 pandemic. Since the first outbreak of the coronavirus, it has spread to more than 180

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nations, causing significant damage to the economy and the job market on a worldwide scale, and isolating about 58% of the world's population.

Table 2.Twitter dataset data distribution and relabelling for our proposed methodology for analysis

Sentiment	Aggregated labels	Count
Extremely Negative	Negative	10962
Negative		19834
Extremely Positive	Positive	13248
Positive		22844
Neutral	Neutral	15426
Total		82314

It is crucial for maintaining mental health and being informed that study be done on people's sentiments andcarry out text classification on the collected data.

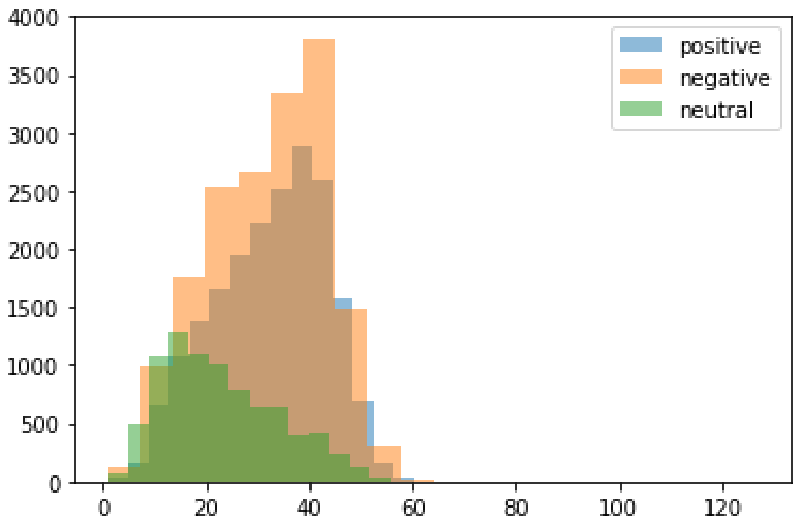


Figure 4. Distributions of word count by sentiment

The tweets were downloaded from Twitter, and after that, human tagging was performed.The following items will be shown in each column: 1) Location2) Tweet At 3) Original Tweet 4) Label. The table 2 shows the Twitter dataset data distribution and relabelling for our proposed methodology for analysis and figures 3 and 4 depict the distribution of word count by sentiment. The Twitter dataset consists of 82314 total data. In this there are 30796 negative data, 36092 positive data and15426 neutral data.

Data pre-processing

After the tweets have been collected, the following pre-processing operations are carried out in order to improve the quality of the raw labelled data as shown in the figure 5. All punctuations, digits, or letters without particular meaning are removed from the dataset, since these additions will not significantly increase the accuracy of the prediction. The hashtag symbols (such as #china, #lockdown, and #Wuhan, amongst others), uniform resource locators, and @users are removed from the tweets since they will not add to the analysis of the messages. The tweets should have any unnecessary newlines, tabs, or spaces removed from them.

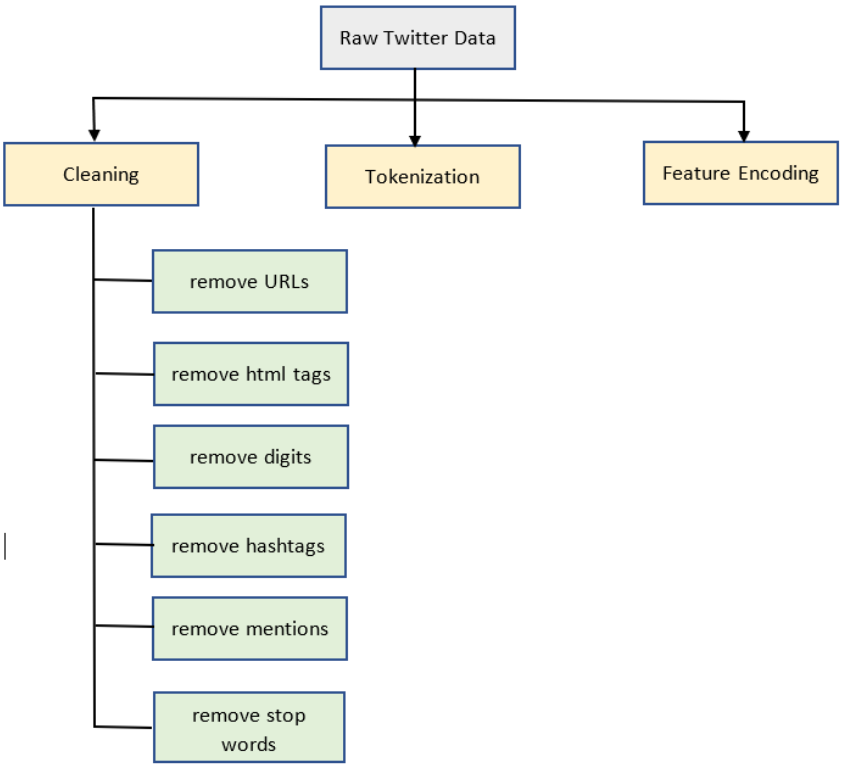
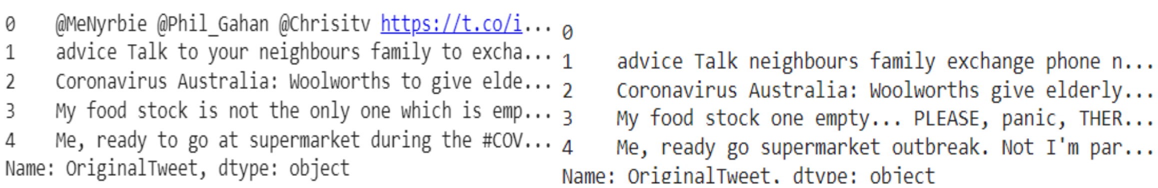


Figure 5. Data pre-processing methods

Stop words are phrases that are often used yet do not provide any data that is important to the study. The use of stop words such as "the," "is," "a," and "an" have been removed. URL links, tags, punctuation, and numbers do not increase the performance of classifiers, despite the fact that they do not provide any new definitions for training systems that would make the feature space more difficult. Simplifying the feature representation requires removing them from consideration. The figure 6 shows the twitter data before and after pre-processing.



(a) Before pre-processing **(b) After Pre-processing**

Figure 6. Before and after pre-processing of Twitter data

The algorithm used for tweet data pre-processing is as follows:

Input: tweet text

R_i = read data()

For R_i != last record

$C_i = R_{i.}$Clean Tweets()

$C_i = C_{i.}$Arrange data()

Tokenizer

End for

The tokenization technique tokened the cleaned text into words to filter out extraneous tokens. The tokenization process is necessary before changing to vectors that are used as input for classifiers. In feature encoding, the sentiments are encoded as 0, 1, and 2. The table 3 depicts the encoding of the sentiments predicted in the tweets.

Table 3. Feature encoding

Sentiment	Encoded
Extremely Negative	0
Extremely Positive	2
Negative	0
Positive	2
Neutral	1

5. Results and discussion

During the portion of the process devoted to analysis, we gained valuable perceptions into the emotional condition of the people in India, as well as into the ways in which feelings differed from one state to another and on a daily basis. The maximum number of words in a sentence from the twitter dataset is presented in figure 7.

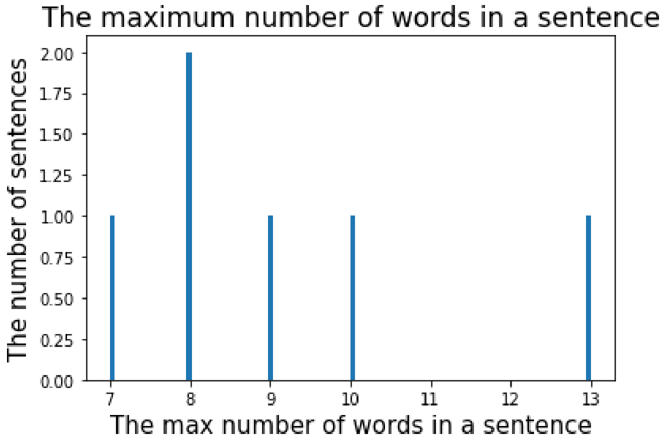


Figure 7. The maximum number of words in the twitter sentence

Using this, the programme verifies the effectiveness of the suggested outfit deep learning model. In this study, we take a look at how well an ensemble-based deep learning model performs. Precision refers to how well a model can correctly identify instances that belong to the positive class, while recall refers to how many of those instances can be predicted positively. The positive id and the positive group are both referred to in these words. Similarly, the "f-score" is a graphical depiction of the weighted harmonic mean of recall and accuracy value. Definition of "prediction accuracy" is the ratio of correctly predicted samples to total samples.

In the context of a classification issue with n groups, if we define $\frac{T_p}{F_p}$ as the True or FalsePositive of the i^{th}class and $\frac{T_n}{F_n}$as the True or False Negative of the i^{th} class, then we can establish some evaluation criteria to quantify the recital of the model as follows**.**

Accuracy (A) is defined as the percentage of samples that are properly categorised relative to the total samples.

$$Accuracy(A) = \frac{\sum_{i=0}^{k} T_{p_i} + T_{n_i}}{\sum_{i=0}^{k} T_{p_i} + T_{n_i} + F_{p_i} + F_{n_i}} \quad (17)$$

The figure 8 depicts the accuracy of our model. The proposed methodology achieves 98% accuracy in sentiment analysis of covid 19, Twitter dataset.

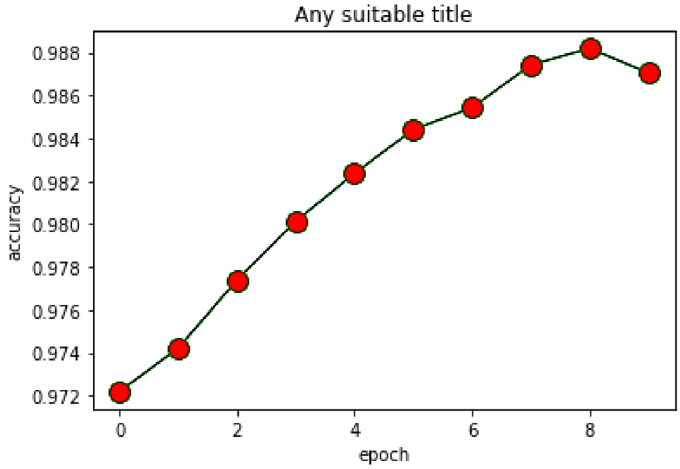


Figure 8. Accuracy of our proposed CBC model

The proposed model achieves the lower loss rate compared to the CNN and LSTM models. It reaches nearly zero. The loss value of the proposed model is shown in the figure 9.

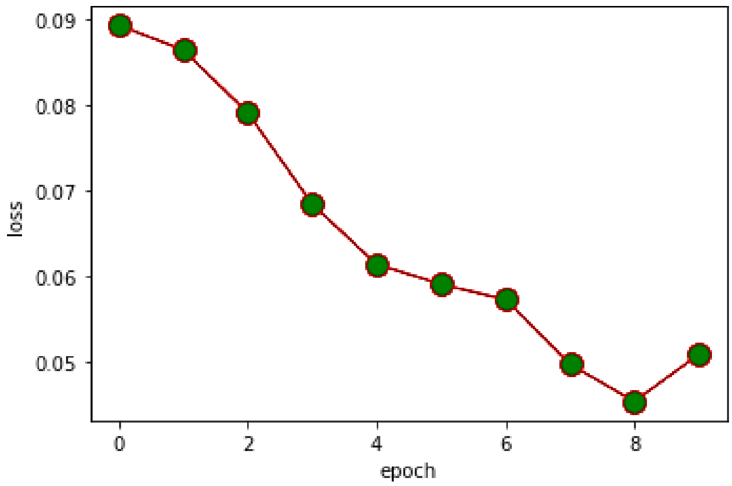


Figure 9. Loss value of our proposed model

The percentage of accurately identified positive samples relative to the total number of samples that were expected to be positive, for the k^{th} class, is referred to as the precision.

$$Precision(p_i) = \frac{T_{p_i}}{T_{p_i}+F_{p_i}} \quad (18)$$

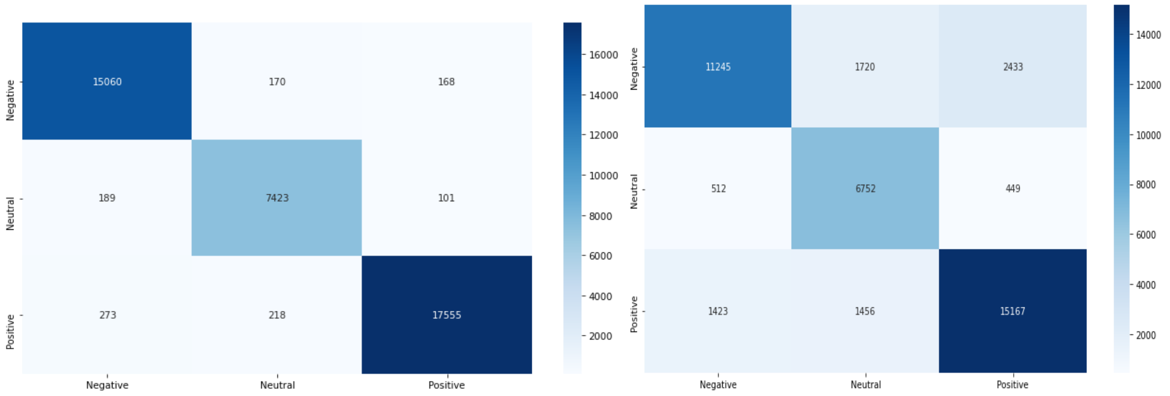
The percentage of positive samples that were properly categorised out of the total number of positive samples for the k^{th} class, is referred to as recall.

$$Recall(r_i) = \frac{T_{p_i}}{T_{p_i}+F_{n_i}} \quad (19)$$

The weighted average of correct responses based on the k^{th} class's accuracy and recall ratings is referred to as F1 score.

$$F1_i = \frac{2\times p_i \times r_i}{p_i+r_i} \quad (20)$$

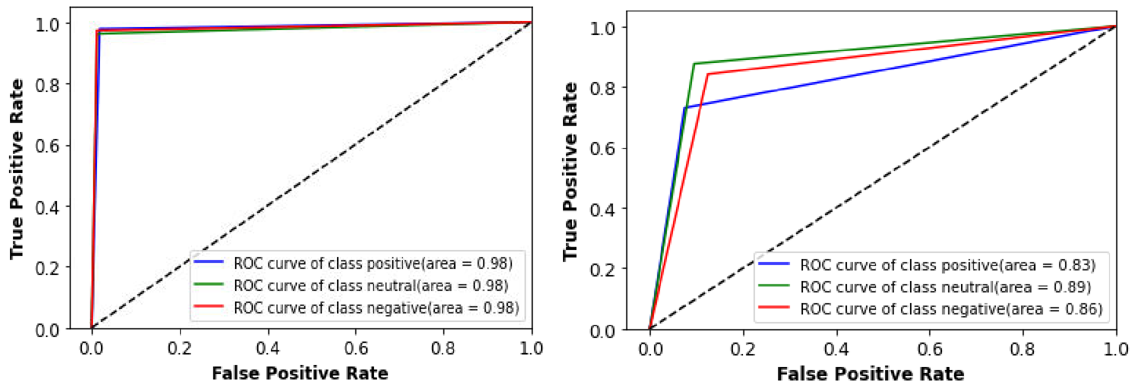
Figure 10 illustrates the true positive, true negative, false positive, and false negative values for the tweet samples that were collected from the dataset. The confusion matrix presents a comparison of the predicted covid sentiments with the actual covid feelings as determined by the dataset. According to the findings that are shown in the confusion matrix that was developed, it is possible to deduce from the data that were obtained that the neutral and negative feelings were categorised with less accuracy in comparison to the positive feelings that were identified.



(a) proposed model CBC **(b) CNN model**

Figure 10. Confusion matrix of our proposed model

The AUC-ROC curve can only be used for issues involving binary categorization. But by applying the One versus All method to classification issues with several classes, we may increase its applicability.As a result, for our three classes labelled 0, 1, and 2, the ROC for class 0 will be calculated by comparing class 0 to the other two classes, namely 1 and 2. The ROC for class 1 will be calculated by first categorising 1 versus not 1, and continuing in this manner. The figure 11 shows the ROC curve of our proposed model.



(a) proposed CBC model **(b) CNN model**

Figure 11. ROC curve for the proposed model

Table 4 shows that our approach outperforms the conventional CNN and LSTM neural network models, suggesting that the ensemble structure can significantly boost sentiment analysis's performance.

Table 4 . Performance comparison with other base line models

Model		**precision**	**recall**	**f1-score**
CNN	Negative	0.85	0.73	0.79
	Neutral	0.68	0.88	0.77
	Positive	0.84	0.84	0.84
	Accuracy			0.81
	Macro Avg	0.79	0.82	0.80
	Weighted Avg	0.82	0.81	0.81
LSTM	Negative	0.90	0.91	0.92
	Neutral	0.92	0.91	0.92
	Positive	0.90	0.90	0.91
	Accuracy			0.90
	Macro Avg	0.92	0.92	0.91
	Weighted Avg	0.90	0.91	0.91
CBC	Negative	0.97	0.98	0.97
	Neutral	0.95	0.96	0.96
	Positive	0.98	0.97	0.98
	Accuracy			0.98
	Macro Avg	0.97	0.97	0.97
	Weighted Avg	0.97	0.97	0.97

The overall performance of the suggested technique can be superior or on par with that of the existing methods when compared to those methods' performance on two datasets. This is due to the fact that our strategy is able to fully use the benefits offered by CNN and Bi-LSTM. Using the multi-channel structure, our technique is able to simultaneously mine sentiment information while simultaneously extracting original and high-level framework information. This allows our method to fully mine sentiment information. In addition, the model is utilised to pay varying amounts of attention to the characteristics of each channel and, appropriately, the global merged features in order for our technique to be able to filter out the appropriate features.

6.Conclusion

Coronavirus, also known as COVID-19, has emerged as the most significant threat to human health in recent years. Researchers and government officials from around the world are working together to find ways to reduce the mortality rate caused by this prevalent disease. This article grants the results of the implementation of a collection of models with the purpose of classifying the attitude expressed in tweets that are posted on the Twitter platform by users. To be more specific, the classifiers are tasked with determining if the attitude expressed in the tweets will be good, negative, or neutral, and the subject matter of the tweets will centre on the COVID-19 epidemic. An experiment is carried out within the context of this piece in order to ascertain the prevalent mindset (sentiment) of the populace. The quality of the data that was obtained is improved by the process of pre-processing the data. Based on the results of the experimental study, the proposed ensemble-based deep learning model (CBC) found superior recital in sentiment estimate in comparison to individual feature extraction methods and classifiers. This was determined by comparing the prediction accuracy, precision, recall, and f1-score of each method. The ensemble-based deep learning model that was suggested, obtained 98% accuracy when it was applied to the analysis of Twitter sentiment.

To choose significant characteristics for the purpose of further enhancing the forecast accuracy with partial increases in computing complexity, a unique hybrid optimization approach might be implemented in the proposed model as a future addition in order to pick such features. In accumulation, the current classifiers might be evaluated using bigger datasets in order to validate the high levels of accuracy that were reached in sentiment analysis. In addition to increasing the total size of the dataset, it is essential to include a greater number of numerical characteristics than were included in the data set that was utilised for the purposes of this study.

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