

Classification of Twitter COVID Tweets Using Deep CNN-SLSTM Technique

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Abstract:

A wide range of industries, including company management, travel and tourism management, education management (E-Learning), the medical field, government agencies, telecommunications management, and private firms, can benefit from user opinion analysis. Many classifiers for deep learning and machine learning are being created to automate sentiment analysis. For sentiment analysis, real-time tweets are initially gathered from various social media platforms like Twitter and Facebook as well as numerous review websites like Amazon and Flip-kart. In this research, a real-time dataset is created using the Twitter API and is used to gather tweets about COVID-based keywords between April 2021 and May 2021. This research utilizes the Deep Convolution Neural Network with Stacked Long Short Term Memory (CNN-LSTM) for sentiment analysis. The performance of CNN-LSTM is compared with six machine learning classifiers, including Naive Bayes, Logistic regression, Support vector classifier, Random forest, and Decision tree, as well as five neural network classifiers, including LSTM, CNN, CNN-LSTM, and Bidirectional LSTM. Metrics like precision, recall, F1-Score, Accuracy, Mean Absolute Error, Root Mean Square Value, R2 score, and Cohen kappa score are used to assess the performance of classifiers. The experimental investigation demonstrates that CNN-SLSTM provides good accuracy (99%) and a good R2 score, a kappa score, and less RMSE score compared with other learning models.

Keywords: *User opinion analysis, Twitter COVID tweets, Convolution Neural Network, Long Short Term Memory.*

INTRODUCTION

Opinion mining or sentiment analysis is a type of data prediction that uses short statements or tweets obtained from social media or online review websites [1,2]. Researchers are now using a variety of natural language processing approaches, machine learning, and deep learning classifiers to predict the opinion or comment from the text. The main purpose of this research is to develop a more accurate and enhanced performance model for such studies. Sentiment analysis is beneficial in a variety of fields. For example, firm management may make product decisions and enhance productivity levels based on customer feedback and market forecasting. Sentiment analysis is also used to predict popular travel and tourism destinations, political debates in government elections and security sectors, best movies, best media articles, best airlines, emotions about diseases, crime detection, and telecommunication management utilizing review text from social media users [3].

In general, sentiment analysis from review text is performed at the document, sentence, and word levels [4]. Several classification algorithms are used to distinguish the text as good, negative, or neutral based on sentiment polarity. There are three methods of sentiment analysis: lexicon-based, machine-learning-based, and hybrid-based. The categorization processes are depicted in Figure 1. Determine the sentiment score by aggregating the sentiment words (sentiment lexicons) in the given text using a lexicon-based technique [5]. Lexicon-based

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sentiment analysis is performed using a dictionary such as VADAR, AFIN, LIWC, or a corpus. Dictionary-based sentiment analysis is time-consuming and inefficient because dictionaries are created by people. As a result, various researchers are working on corpus-based sentiment analysis [6]. To solve the issue of words with similar contexts but opposing sentiment polarities, a corpus-based approach generates context-specific or domain-specific lexicons. Lexicon-based techniques, on the other hand, are constrained since they ignore textual order, implicit properties, sequence length, and complicated logic. Machine learning-based sentiment analysis is now used by researchers for sentiment text classification [7]. When compared to lexicon-based models, machine learning-based sentiment analysis learns more complex meaning, and once learned, machine learning classifiers can be employed anytime needed. Machine learning models can be classified as supervised, reinforced, or unsupervised. To categorize sentiment text, numerous conventional machine learning classifiers, such as Naive Bayes(NB), Logistic Regression(LR), Decision Tree (DT), Random Forest(RF), Support Vector Machine(SVM), and deep neural network models, are employed. Deep neural network models known as deep learning models [8] such as Convolution Neural Network (CNN), Long Short Term Memory (LSTM), Bidirectional LSTM, and a combination of LSTM and CNN have been widely employed for sentiment analysis in recent years. Deep learning models [9] employ word embedding as input, which increases text performance. For sentiment analysis, a hybrid technique combines both lexicon-based and machine learning-based approaches [10].

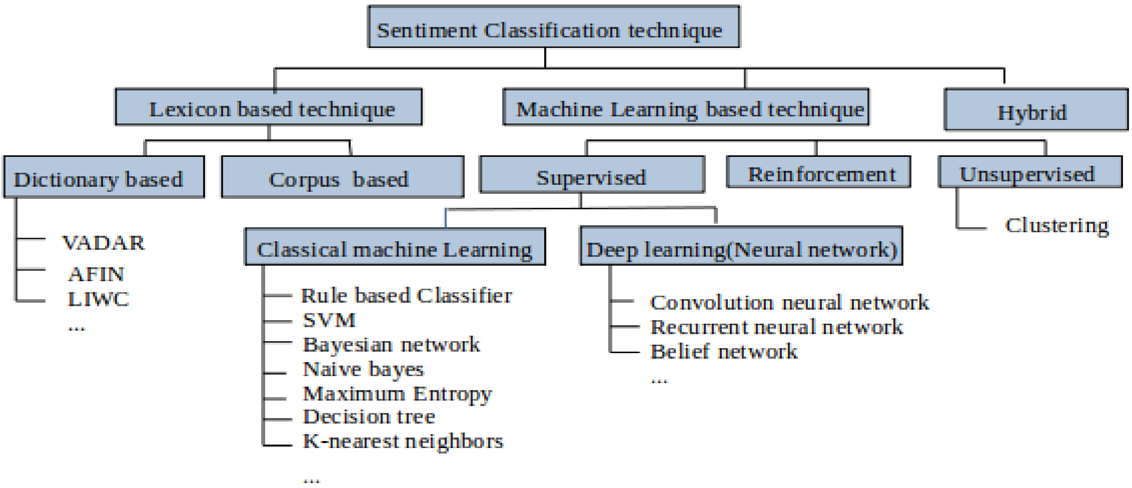

Figure1. Categorization of Sentiment classification technique

This paper is structured as follows: First discusses the work that has already been done in user opinion analysis based on machine learning and deep learning models. The proposed CNN-stacked LSTM model for tweet analysis on the Twitter dataset is then discussed. Finally, the experimental results for COVID tweet categorization are presented. The performance of the classifier is assessed using the standard performance metrics precision, recall, accuracy, and the F1-score. This section evaluates the performance of the classifier using additional statistics measures like the AUC score, RMSE, MAE, r2 score, and Kappa Score. From this analysis, find the best classifier that is appropriate for opinion mining on user text reviews.

LITERATURE REVIEW

Review of Machine learning techniques in User Opinion analysis

Because of the sarcasm, ambiguous words, multi-polarity words, dependencies, and inconsistencies that arise in sentiments or review text [11], social media data analysis is a difficult task. Several research projects are being carried out to address these issues. One of the better solutions is to use natural language processing and machine learning techniques for sentiment

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classification. This section examines the machine learning approaches used for sentiment analysis on various types of applications.

Ahmed et al. [12] have used machine learning approaches to analyze sentiment in food product reviews. They gathered Amazon reviews and classified them using linear SVM, NB, and LR. According to their findings, the linear SVM outperforms other models in terms of accuracy by more than 80%.

Luo X et al [13] have used text classification to classify reviews from news sources. For classification, they employ NB, LR, SVM, and LR-CV. They evaluate the classifier's performance in terms of precision, recall, f1-score, and accuracy. According to their findings, SVM outperforms other models in terms of precision. Abdulkareem [14] conducted sentiment analysis on a collection of COVID-19 word vaccination data. For categorization, they utilize decision trees, KNN, Random Forest (RF), and NB. According to their findings, DT outperforms other models in terms of accuracy by more than 85%. Khanday et al [15] performed binary categorization of COVID-19-related Tweets obtained from the Twitter domain. They used classifiers such as DT, SVM, and Multinomial NB to conduct classification. According to their findings, DT outperform other models in terms of accuracy.

Hanswal et al [16] have conducted opinion mining on E-learning and MOOC data obtained from the Twitter website. SentiWordnet determines the sentiment polarity. They used classifiers such as NB, LR and SVM to perform classification. According to their findings LR outperforms other models in terms of accuracy (over 70%). Ghiassi, M., et al. [17] have performed user opinion analysis on datasets from Starbucks, Verizon, and Southwest Airlines. They employ unsupervised learning classifiers such as Yet Another Clustering and KNN. According to their findings, YAC2 outperforms all other datasets.

Li H et al [18] have used machine learning classifiers NB, KNN, and SVM to assess 4300 emotions published on dating websites. They use a lexicon as well as a machine learning approach to analyze individual behavior for sentiment analysis.

Review of Deep learning techniques in User Opinion analysis

Deep learning models have received a lot of interest in recent years for analytical prediction in a variety of applications. The precision and self-learning capability of neural network models make them suited for processing massive amounts of text, images, and video. This section explains the many types of deep learning models that are used for user opinion analysis.

Nemes et al. [19] have used a Recurrent Neural Network (RNN) to determine emotional polarity on a given topic during a specified time interval. Using the Twitter API, they create a topic-based dataset. They compare the binary classification performance of text blobs and RNNs. Albadani et al [20] have used a RNN model along with a SVM for user opinion analysis on the Twitter US Airline data set. They used LSTM for user opinion prediction and SVM classifier instead of softmax layer. Grid search is applied for feature selection. They evaluate the performance of the deep learning model and SVM classifier in terms of accuracy and F1-Score.

Lee H et al. [21] have developed a dimensional approach to user opinion analysis using a Chinese Twitter dataset. There are 5,512 words in this dataset, as well as 2,998 multiword phrases, 2,582 single sentences, and 2,969 multi-sentence texts. They employ a corpus-based approach as well as machine learning techniques such as LR, SVM, CNN, RNN, LSTM, Attention Based Neural Network, XLNet, and the BERT model. They assess the model's performance using the mean absolute error (MAE) and Pearson Correction Coefficient (r). According to their findings, the BERT model outperforms all other machine learning methods.

Seki, K., et al. [22] have devised a method for measuring business mood based on newspaper article analysis. Using sentiment analysis, they compute the S-APIR index based on sentiment score. To estimate the business sentiment score of text, they employ a pre-trained Japanese BERT model. They utilize a one-class Support vector machine to filter dissimilar documents and a TFID vectorizer to extract features. They compare the performance of the BERT

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model with that of the LSTM-BiRNN. Precision, recall, F1 score, and correlation index are used to assess model performance.

For medical text classification, Liang et al [23] have employed a double channel Long Short-Term Memory Model. For sentiment analysis, they employ cMedQA and the Sentiment 140 Twitter dataset. It employs both a word-level and a char-level embedding technique. It enhances classification model accuracy when compared to CNN-LSTM, and the model is evaluated based on precision, recall, F1 score, and accuracy. To perform classification, Taware, R et al [24] devised a black box technique based on keywords and n-grams. They increase classification performance by rearranging words in a training data set and evaluate classifier accuracy by augmenting generic phrases from the Wikipedia data set.

Onan A et al [25] created a term weighted neural language model and a Stacked bidirectional LSTM model for detecting sarcasm in news headlines. It employs an automatic filtering process to clean the data set using word embedding methods such as Word2vec, Fast text, and Glove, as well as a trigram model, to extract features. The suggested Stacked Bidirectional LSTM model outperforms CNN, RNN, CNN-LSTM, and Stacked LSTM models in terms of accuracy.

Nguyen et al. [26] executed aspect-based sentiment analysis in a Smartphone dataset using Bidirectional LSTM with a Conditional Random Field Layer. For sentiment analysis on airline datasets, Jain et al. [27] have employed a convolution neural network with long short term memory.

Al Bataineh et al. [28] have used a Colonel Selection Algorithm (CSA) for feature selection and an LSTM network for classification. For sentiment categorization, they employ the IMDB movie review data set, SMS Spam, and Twitter US Airline Dataset. CSA-LSTM performance is compared to that of machine learning classifiers such as RF, LR, SVM, and MNB

Mahajan R et al [29] used Twitter to collect tweets from five distinct areas of India to evaluate the crime intensity across the region. The sentiment140 dataset is used for the evaluation. of text. The Bidirectional LSTM is utilized for sentiment analysis and has an accuracy of 84.74%. Tan et al. [30] created Dynamic Embedding Projection gated CNN (DEP-CNN) for Text Classification. Initially, the DEP-CNN transforms text and controls the context information-related word embedding matrix using a dynamic embedded projection gate. Finally, text classification is performed using the CNN layers. For text classification, the DEP-CNN makes use of the IMDB, AG News, AAPD, and Reuters datasets.

Mao S et al [31] created an LSTM and Topic CNN model for classifying online Chinese medical inquiries. For classification, they employ the data sources Ask39 and 120 ask. The word embedding approach generates the text word vector, and the CNN is applied to extract text features from the text. The text features are categorized using the LSTM model to detect multi-class labels such as heart illness, hypertension, dermatology, orthopedics, and so on.

P.F. Muhammad et al. [32] have conducted sentiment analysis on Indonesian hotel reviews. For sentiment categorization, they employ a word2vec-based LSTM. They compare the LSTM by changing factors such as pooling method (Max Pooling and Average Pooling), drop-out ratio (0.2, 0.5, and 0.7), and learning rate values.

According to this literature review, neural network-based models (also known as deep learning) are useful in analyzing input sequences of words from attitudes. When compared to other models, the LSTM model provides the highest level of accuracy. The proposed work employs a Convolution Neural Network with Stacked Long Short-Term Memory (CNN-SLSTM) model for tweet sentiment analysis on the COVID data set. Using the Max pooling method, the convolution neural network [33,34] is chosen for enhanced feature selection and extraction. The Stacked LSTM is used to find long-term relationships between sentiment terms in large amounts of text[35]. The performance of a Convolution Neural Network-based stacked Long Short-Term Memory model is compared to that of other deep learning models such as CNN, LSTM, Bidirectional LSTM, Stacked LSTM, and CNN with LSTM models.

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METHODOLOGY

Convolution Neural Network with Stacked LSTM model

This section presents the proposed supervised learning methodology, Convolution Neural Network with stacked LSTM (CNN-SLSTM), for Twitter user opinion analysis on the COVID Tweets. COVID twitter dataset is initially produced by collecting tweets from Twitter, followed by preprocessing to clean the tweets and eliminate multilingual text. After preprocessing the tweets, use the keras tokenizer to turn the text sequence into an integer encoded sequence [36]. For classification, the input word sequence is transferred to the CNN-SLSTM layer. Figure 2 shows the flow of CNN-SLSTM approach.

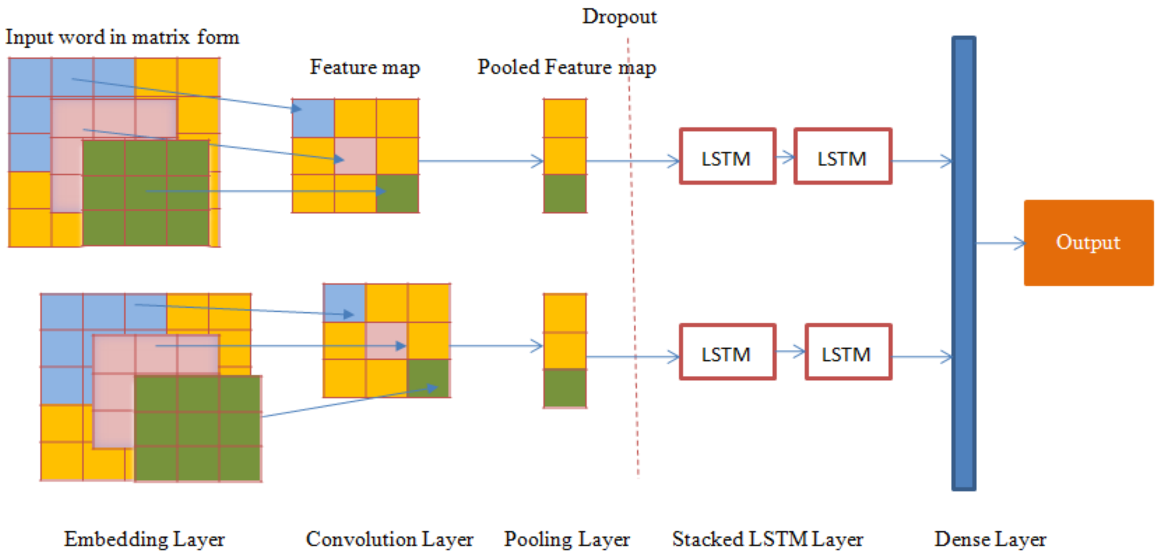

Figure 4: Structure of the CNN-SLSTM model

Preprocessing

Preprocessing is the first and most important step before performing any analysis on real-time data sets. This is required to remove null data, outliers, noise, and inconsistencies from the data set [37]. The raw text is gathered from Twitter using Twitter API and tweepy. It uses 7 different keywords such as corona, covid, vaccine, covid 19, covaxine, lockdown and virus for tweets collection from Twitter. The raw text has been pre-processed by natural language processing techniques. The following steps are carried out one by one.

1) Removing superfluous hashtags @isbonTuscono, @omni du, and linkages like http, https, rt.
2) Remove any square bracketed text, special characters, and punctuation.
3) Remove duplicate rows and rows with multilingual text.
4) Perform word segmentation on concatenated terms, such as coronacases, which should be corona, cases, and Covidvirus, which should be Covid, virus.
5) Removing unneeded stop words such as co, de, da, and amp that cause noise in textual data.
6) On text, do stemming, Lemmatization, and lexicon normalization.

Following preprocessing, the tokenizer converts the text sequence into integer encoded sequence form, 2000 words at a time, and utilizes zero padding to make the sentence equal in length. It uses the standard scalar method to standardize text features.

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CNN –Stacked LSTM

The CNN stacked LSTM (CNN-SLSTM) has a layer of units that classify sentiment text as positive or negative. Each unit in a layer receives several inputs, the weights of each input, and applies an activation function to the sum of the weighted inputs to produce an output that is transferred to units in the next layer. The proposed method builds neural networks by stacking layers together using the Keras sequential model. For classification, the proposed CNN-SLSTM utilizes the successive layers listed below.
1. Word embedding layer
2. Convolution Layer
3. Pooling layer
4. Stacked LSTM layer
5. Dense layer

Word embedding Layer:

In deep learning models for text processing, the Word Embedding Layer is powerful layer. It receives input from the tokenizer, which turns words into vector values. This layer effectively obtains the vectors for each word in a sentiment sequence. This layer provides dense vector representation, which aids in conveying the semantic meaning of words [38]. After vectorizing the word, use a 1D convolution layer to extract the features and a kernel that goes in one direction.

Convolution Layer:

The convolution layer gathers features from the embedding layer and generates a feature map for each input matrix. Here, the convolution filter size is 32, and the kernel size is 3. For feature extraction, the ID convolution layer employs the Relu activation function. The feature map is created by the 1D convolution layer using a convolution filter. To obtain a pooled feature map, the feature map is transferred to the pooling layer. To avoid overfitting during the convolution phase, 1D max pooling with pool size 2 is used. The spatial dropout 1D (0.4) reduces the number of computations by deleting unnecessary output units from the network. Following the pooling operation, input is sent to a two-level stack LSTM (LSTM 1 of size 64, LSTM 2 of size 32).

Stacked LSTM Layer:

Stacked LSTM process input sequences in several LSTM layers. For word sequences, LSTM uses a distributed representation of words in conjunction with a probability function. In this case, a two-level LSTM is employed to learn text long-term sequence prediction. The output of level 0 LSTM is transferred to the level 1 LSTM layer for the prediction of new data. The calculation performed at level 0 is described below by equation [1-6].

$$i^a = \sigma((W_i^a \times h_{t-1}) + (U_i^a \times x_t)) \tag{1}$$

$$f^a = \sigma\left(\left(W_f^a \times h_{t-1}\right) + \left(U_f^a \times x_t\right)\right) \tag{2}$$

$$o^a = \sigma\left((W_o^a \times h_{t-1}) + (U_o^a \times x_t)\right) \tag{3}$$

$$g^a = \tanh\left(\left(W_g^a \times h_{t-1}\right) + \left(U_g^a \times x_t\right)\right) \tag{4}$$

$$c_t^a = \left((c_t^{a-1} \circ f^a) + (g^a * i^a)\right) \tag{5}$$

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$$h_t = \tanh(c_t^a) \circ o^a \quad (6)$$

The calculation done in level 2 is described by the equations [7 to 12].

$$i^b = \sigma\left(\left(W_i^b \times k_{t-1}\right) + \left(U_i^b \times x_t\right)\right) \quad (7)$$

$$f^b = \sigma\left(\left(W_f^b \times k_{t-1}\right) + \left(U_f^b \times x_t\right)\right) \quad (8)$$

$$o^b = \sigma\left(\left(W_o^b \times k_{t-1}\right) + \left(U_o^b \times x_t\right)\right) \quad (9)$$

$$g^b = \tanh\left(\left(W_g^b \times k_{t-1}\right) + \left(U_g^b \times x_t\right)\right) \quad (10)$$

$$c_t^b = \left(\left(c_t^{b-1} \circ f^b\right) + \left(g^b * i^b\right)\right) \quad (11)$$

$$k_t = \tanh\left(c_t^b\right) \circ o^b \quad (12)$$

For a particular timestamp, the output is obtained by combining both hidden state information of both levels by equation [13].

$$o = U^0\ h_t + W^0\ \ k_t + \ b^0 \quad (13)$$

Dense Layer:

The dense layer is also known as the fully connected layer because all neurons in the preceding LSTM layer are coupled to all neurons in the dense layer. Following the output of the LSTM, the result is sent to the dense layer, which uses the sigmoid function to confine the output to between 0 and 1 for the positive or negative class.

$$P\left(\frac{y}{x}\right) = \text{sigmoid}\ (W_s \times \text{o} \ + b^s\ ) \quad (14)$$

$$y' = argmax_y\ P(y\ /\ x\ ) \quad (15)$$

The proposed sequential model CNN-SLSTM is compiled by using the Adam optimizer. The overall process is illustrated in algorithm1.

Algorithm 1. CNN-Stacked LSTM model

Input : {T1,T2,T3 … Tn} is a collection of tweets or short message text
Output : {0,1} where 0 refer positive tweet and 1 refer negative tweet
Begin
for each T_i tweet from the text and d be the maximum dimension do
$T_i^w = word\ Embedding$ (Ti)
for each word $n_i \times$ d in the word vector matrix of T_i^w do
$T_i^c = CNN$ (Ti) #Get feature map by convolution filter and extract most important features by pooling
for each vector of in T_i^c do

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$T_i^L = LSTM$ (Ti) # extract features using LSTM 1
$T_i^M = LSTM$ (T_i^L) # extract features using LSTM 2
y_i = softmax (Ti) # classify the text and categorize tweets
end
end
end

RESULTS AND DISCUSSION

Tweets about COVID were gathered from the Twitter API using tweepy during April and May 2021, based on keywords. In this study, Covid, Corona, Lockdown, and Covid vaccination, corona cases, and coronavirus are some keywords chosen for tweet collection. A total of 1500 COVID reviews have been gathered from the Twitter website. Experiments were carried out by a Google collaboratory that ran code in the Google cloud. In this case, 70% of tweets were chosen for training and 30% for validation.

Experiments utilize nltk, the regular expression (re) package for pre-processing, and Keras with the Tensor flow backend for neural network creation. Using Text Blob, the sentiments are first classified as positive, negative, or neutral tweets. The pie graphic in Figure 3 depicts 25.7 percent positive tweets, 22.3 percent negative tweets, and 52.0 percent neutral tweets from a total of 20000 messages. Figure 4 depicts a word cloud created from gathered tweets. Figure 5 depicts the top ten words culled from Tweets.

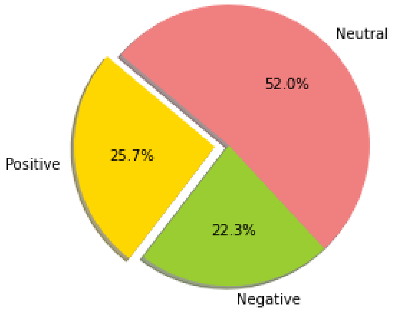

Figure 3. Pie-chart for classified tweets

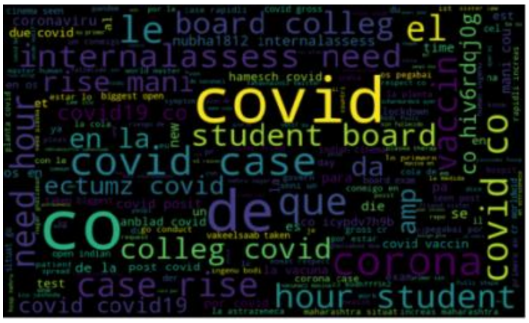

Figure 4. The word cloud for Tweets

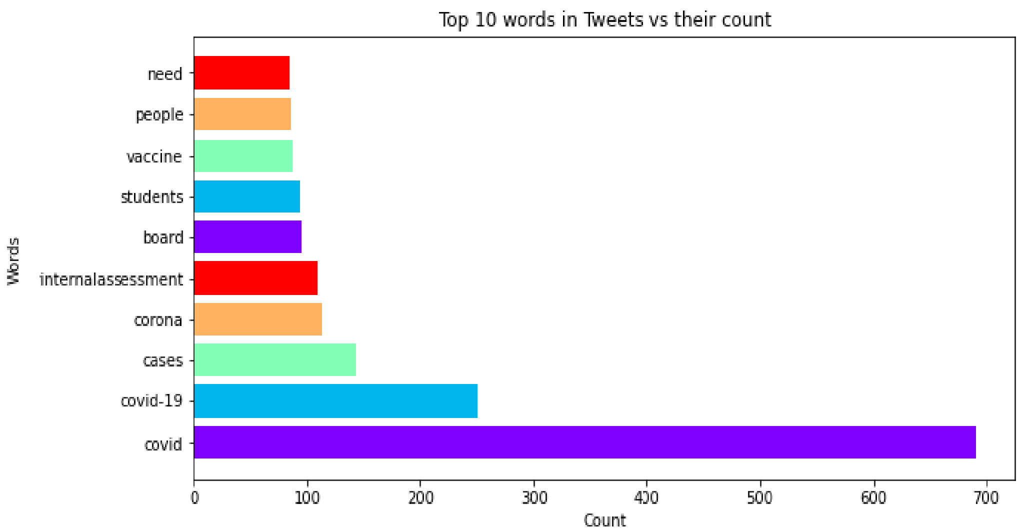

Figure 5. Top 10 words collected from tweets and their count

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The rows of collected raw tweets and pre-processed tweets are shown in Figure 6 and Figure 7.

	Unnamed: 0	tweet_id	text	favorite_count	retweet_count	created_at
0	0	1380731649508343808	Canadian Medical Association Foundation COVID-...	0	0	Sat Apr 10 03:57:32 +0000 2021
1	1	1380560510836473857	RT @MissCyclingNow: MISSISSAUGA CYCLING ADVISO...	0	3	Fri Apr 09 16:37:30 +0000 2021
2	2	1380558211829403651	RT @MissCyclingNow: MISSISSAUGA CYCLING ADVISO...	0	3	Fri Apr 09 16:28:21 +0000 2021
3	3	1380557728477810688	RT @MissCyclingNow: MISSISSAUGA CYCLING ADVISO...	0	3	Fri Apr 09 16:26:26 +0000 2021
4	4	1380553432474476549	MISSISSAUGA CYCLING ADVISORY CMTE: Tues April ...	4	3	Fri Apr 09 16:09:22 +0000 2021
5	5	1380365357144244225	RT @oldbid45: @JoanneF90221509 @VictoryDay_Hop...	0	50	Fri Apr 09 03:42:01 +0000 2021
6	6	1380189258061914119	Immigration detention is rarely justified and ...	1	0	Thu Apr 08 16:02:16 +0000 2021
7	7	1379557130609524736	RT @SamCraggsCBC: Coming up tomorrow at Hamilt...	0	1	Tue Apr 06 22:10:25 +0000 2021
8	8	1379532625510031360	Coming up tomorrow at Hamilton's general issue...	4	1	Tue Apr 06 20:33:03 +0000 2021

Figure 6. Collected raw tweets without pre-processing

	Unnamed: 0	tweet_id	text	favorite_count	retweet_count	created_at
0	1	1392707397450410000	Double trouble: Exploring the labour market an...	0	0	Thu May 13 05:04:53 +0000 2021
1	2	1392707396695430000	Some news is good, some bad, some mixed.The n...	0	716	Thu May 13 05:04:53 +0000 2021
2	3	1392707396271630000	Dr. Sellin is exposing all scientists who hav...	0	146	Thu May 13 05:04:53 +0000 2021
3	4	1392707395596560000	The pandemic and widespread frustration over u...	0	4	Thu May 13 05:04:53 +0000 2021
4	5	1392707395504200000	BREAKING. No10 admits internal Whitehall less...	0	807	Thu May 13 05:04:52 +0000 2021
5	6	1392707395261010000	i am getting my covid shot on Sunday i wa...	0	26	Thu May 13 05:04:52 +0000 2021
6	7	1392707395256650000	Also please let me know one thing some of the ...	0	0	Thu May 13 05:04:52 +0000 2021
7	8	1392707395135040000	Overnight Covid shift at FMC and here are the ...	0	46	Thu May 13 05:04:52 +0000 2021
8	9	1392707395046930000	Rs.18,000 Crores of FCRA money is in Bank FDs ...	0	577	Thu May 13 05:04:52 +0000 2021
9	10	1392707394778520000	IndianExpress Letter to PM from opposition, fo...	0	0	Thu May 13 05:04:52 +0000 2021

Figure 7. Collected Tweets after pre-processing

Determine the polarity and subjectivity scores of the gathered tweets using Text Blob. We discovered 10400 tweets with positive polarity and 9560 tweets with negative polarity, as well as 11642 objective counts, 5852 subjective counts, and 1139 neutral counts based on subjectivity. The polarity and subjectivity of sentiment text are shown in figure 8 and Figure 9.

text	favorite_count	retweet_count	created_at	polarity_score	polarity	subjectivity_score	subjectivity
Double trouble: Exploring the labour market an...	0	0	Thu May 13 05:04:53 +0000 2021	-5.000000e-02	negative	0.200000	objective
Some news is good, some bad, some mixed.The n...	0	716	Thu May 13 05:04:53 +0000 2021	5.551115e-17	positive	0.633333	subjective
Dr. Sellin is exposing all scientists who hav...	0	146	Thu May 13 05:04:53 +0000 2021	-5.000000e-02	negative	0.000000	objective
The pandemic and widespread frustration over u...	0	4	Thu May 13 05:04:53 +0000 2021	0.000000e+00	neutral	0.000000	objective
BREAKING. No10 admits internal Whitehall less...	0	807	Thu May 13 05:04:52 +0000 2021	0.000000e+00	neutral	0.000000	objective

Figure 8. Polarity Score and Subjectivity Score of Tweets

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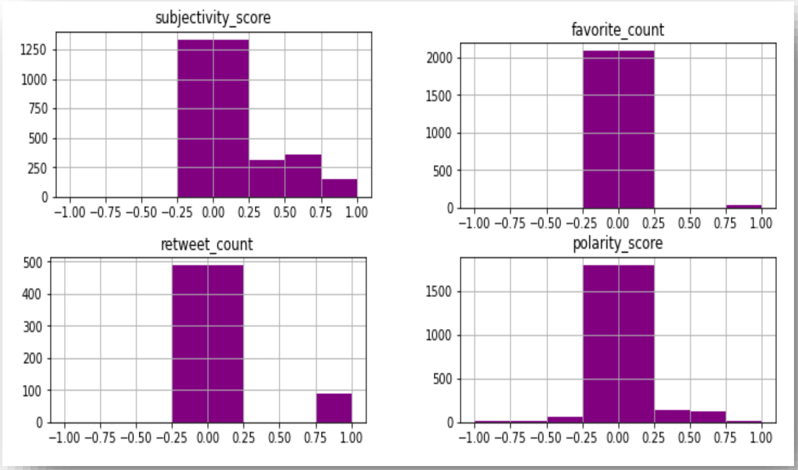

Figure 7.Subjectivity score, favorite count, tweet count, and Polarity score of Tweets.

Keras sequential model generates a neural network for sentiment classification. The proposed CNN-SLSTM is trained using 70% of the COVID Twitter data set and validated using 30% of the COVID Twitter data set. Precision, recall, F1 score, and training and testing accuracy are used to assess CNN –SLSTM performance. CNN-SLSTM performance is evaluated by other important metrics Mean Absolute Error, Root Mean Square Value and Cohen kappa score, and r2 score.

Evaluation Parameters

The performance of the classifier is evaluated by the following metrics.

1. **Accuracy**: The accuracy specifies the number of correctly classified COVID Twitter data samples from the total samples in a dataset. It is calculated by equation (16)

$$\text{Accuracy} = \frac{(\text{True Positive} + \text{True Negative })}{(\text{True Positive} + \text{True Negative } + \text{False Positive } + \text{False Negative })} \quad (16)$$

Here True positive refers to COVID Twitter data samples that were initially classified as positive and are also expected to be positive. False Positive specifies the data samples that are initially identified as negative but are predicted to be positive. True Negative refers to COVID Twitter data samples that were initially categorized as negative and that the classifier predicted to be negative. False Negative applies to COVID Twitter data samples that are initially positive but are expected to be negative.

2. **Precision:** Precision specifies the proportion of true COVID tweets from the total positive tweet samples in a dataset. It is calculated by equation (17)

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \quad (17)$$

3. **Recall:** Recall specifies the proportion of true positive rate of COVID tweets samples. It is calculated by equation (18).

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$$Recall = \frac{True\ Positive}{True\ Positive\ + False\ Negative} \quad (18)$$

4. **F1-Score:** The F1 score is evaluated from both Recall and Precision. It specifies the harmonic mean of Recall and Precision. This is evaluated by equation (19)

$$\text{F1 score} = \frac{2 \times (\text{Recall} \ \times \text{Precision})}{\text{Recall} + \text{Precision}} \quad (19)$$

5. **Mean Absolute Error :**

$$MAE = \frac{1}{N} \sum_{I=1}^{N} |Y_{TEST} - Y_{PREDICTED}| \quad (20)$$

6. **Root Mean Square Value**

$$\text{RMSE} = \sqrt{\text{MAE}} \quad (21)$$

7. **r2 score**

$$R^2 = 1 - \frac{\sum(Y_{TEST} - Y_{PREDICTED})^2}{\sum(Y_{TEST} - Y_{MEAN})^2} \quad (22)$$

8. **Cohen kappa score**

$$\text{Kappa score } \ k = \frac{(P_0 - P_e)}{(1 - P_e)} \quad (23)$$

The classification report and accuracy obtained for machine learning and deep learning classifiers are shown in Table 1 and Table 3. According to this table, the proposed CNN-Stacked LSTM model has a higher accuracy of 0.91 for the validation data set. Deep learning classifiers outperform machine learning classifiers in terms of accuracy. Similarly, for additional criteria such as Precision, recall, and F1-score, deep learning classifiers do well. The proposed Deep CNN-Stacked LSTM classifier achieves 0.87 precision, 0.80 recall, and 0.79 F1-score for class 1 and 0.93 precision, 0.94 recall, and 0.93 F1-score for class 2, which is higher than the other classifiers.

TABLE 1. Classification report and accuracy of Machine Learning classifiers

Classifier	Label	Precision	Recall	F1-Score	Support	Training Accuracy	Testing Accuracy
Bernoulli Naïve Bayes	0 1	0.90 0.66	0.86 0.73	0.88 0.69	543 654	0.83	0.8264
Multinomial Naive Bayes	0 1	0.84 0.80	0.95 0.52	0.90 0.63	543 654	0.84	0.8372
Logistic Regression	0 1	0.79 0.82	0.92 0.28	0.88 0.43	543 654	0.8	0.8
Linear Support vector	0 1	0.89 0.82	0.91 0.67	0.92 0.74	543 654	0.84	0.82
KNN	0 1	0.82 0.69	0.91 0.40	0.90 0.57	543 654	0.8372	0.83
Decision tree	0 1	0.89 0.71	0.90 0.69	0.89 0.70	543 654	0.842	0.83

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TABLE 2. Performance analysis of Machine Learning classifiers

ML Classifier	AUC Score	MSE	R2 score	MAE	Cohen's Kappa Score
Bernoulli Naïve Bayes	0.83	0.387	0.40	0.15	0.54
Multinomial Naïve Bayes	0.84	0.424	0.37	0.18	0.56
Logistic Regression	0.8	0.360	0.49	0.13	0.57
Linear Support vector	0.84	0.538	-0.16	0.28	0.42
KNN	0.83	0.424	0.29	0.18	0.58
Decision tree	0.84	0.560	0.50	0.13	0.59

TABLE 3. Classification report and Accuracy of Deep Learning classifiers

Deep Learning Classifier	Label	Precision	Recall	F1-Score	Support	Training Accuracy	Testing Accuracy
LSTM	0 1	0.93 0.70	0.88 0.80	0.91 0.75	543 654	0.987	0.883
Bidirectional LSTM	0 1	0.89 0.84	0.96 0.64	0.92 0.73	543 654	0.987	0.8817
Stacked LSTM	0 1	0.91 0.80	0.94 0.72	0.93 0.76	543 654	0.987	0.8883
CNN	0 1	0.87 0.82	0.96 0.57	0.91 0.67	543 654	0.96	0.863
CNN-LSTM	0 1	0.92 0.76	0.94 0.76	0.93 0.78	543 654	0.987	0.883
CNN-Stacked LSTM	0 1	0.93 0.87	0.94 0.80	0.93 0.79	543 654	0.99	0.91

TABLE 4. Performance analysis of Deep Learning Classifier

DL Classifier	AUC Score	RMSE	R2 score	MAE	Cohen's Kappa Score
LSTM	0.86	0.37	0.25	0.14	0.75
Bidirectional LSTM	0.87	0.34	0.22	0.11	0.77
Stacked LSTM	0.88	0.36	0.23	0.13	0.78
CNN	0.86	0.34	0.13	0.12	0.76
CNN –LSTM	0.88	0.28	0.52	0.135	0.72
CNN –Stacked LSTM	0.90	0.28	0.58	0.08	0.80

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Accuracy curves of deep learning classifiers are displayed below for each epoch. From this analysis, the proposed methodology CNN-SLSTM gives better accuracy among all models.

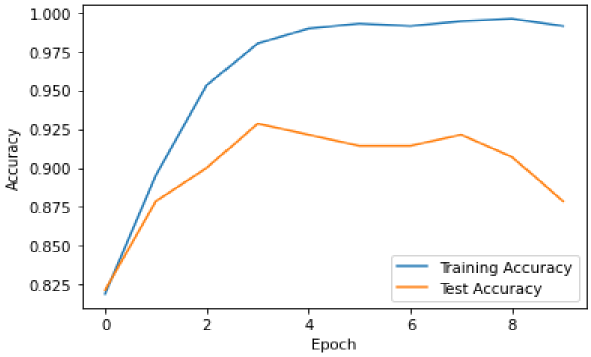

Figure 8 a. LSTM

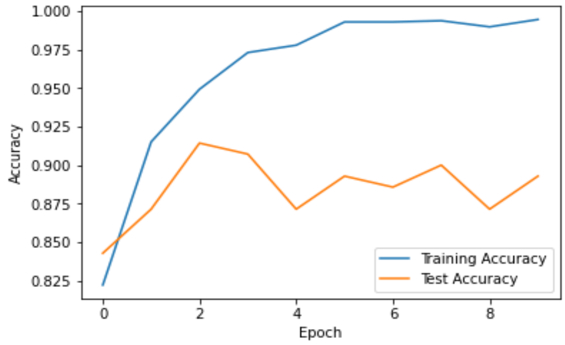

Figure 8 b. Bidirectional LSTM

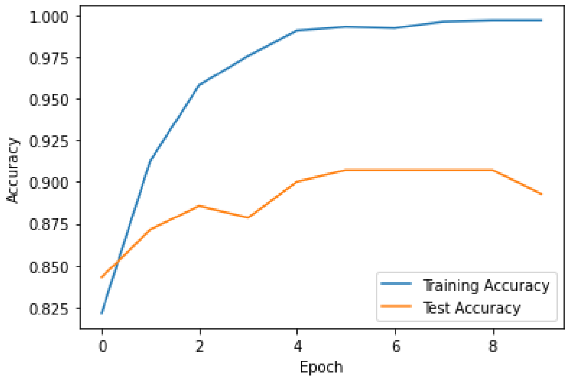

Figure 8c. Stacked LSTM

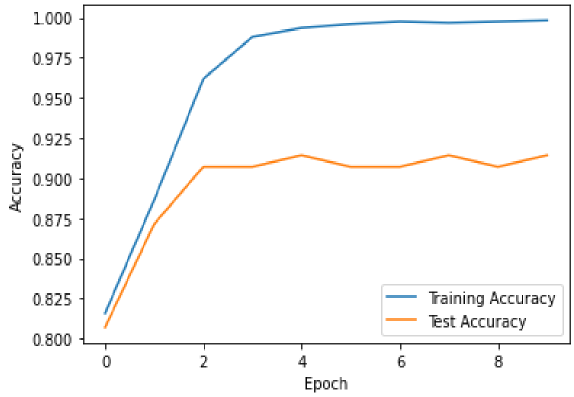

Figure 8c. CNN

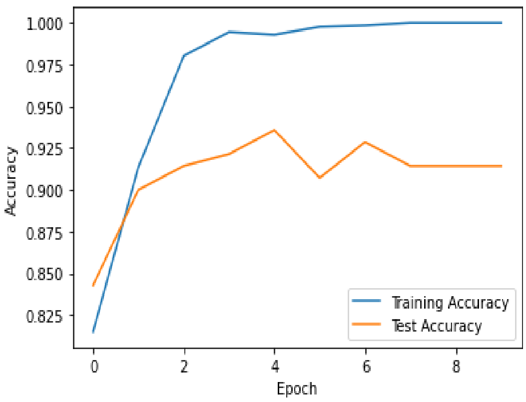

Figure 8e. CNN and LSTM

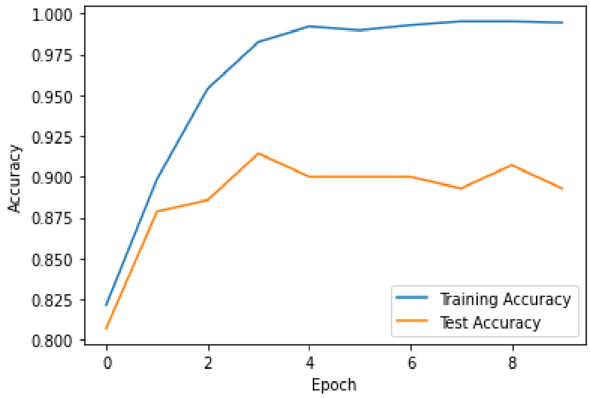

Figure 8f. CNN and Stacked LSTM

Deep Learning models provide higher accuracy, precision, recall, F1-score, and AUC Score compared with Machine learning approaches. From DL approaches, CNN-stacked LSTM provides higher accuracy for the training data set (99%) and test data set (91%). Similarly, Deep learning models provide a high AUC score (0.90) compared with Machine learning models (0.84). The RMSE (Root Mean Square) value of CNN-Stacked LSTM (0.28) is low compared with other machine learning approaches (minimum is 0.36) CNN-Stacked LSTM provides a good R2 value

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(0.58) and good kappa score value (0.80) compared with other models. From this analysis, CNN-Stacked LSTM provides a good prediction for this user opinion analysis.

CONCLUSION

User Opinion analysis is performed on the COVID tweet data set to identify the opinions as positive or negative. The real-time data set is initially created by scraping data from Twitter, and then preprocessing is performed to clean the text and eliminate multilingual text to speed up the sentiment prediction process. The CNN-SLSTM is designed to conduct sentiment categorization tasks. CNN-SLSTM combines the benefits of both Convolution Neural Network and LSTM models for feature selection and long-term sequence prediction. CNN-SLSTM performance is compared to that of various deep learning methods such as LSTM, CNN, Bidirectional LSTM, BiLSTM, and CNN-LSTM. Various metrics, including precision, recall, f1 score, training accuracy, and validation accuracy, are used to assess classifier performance. CNN-SLSTM is compared to other machine learning approaches such as Nave Bayes, Decision Tree, Logistic Regression, Linear SVC, and KNN. According to this investigation, CNN-SLSTM outperforms other learning models by providing 99 % training accuracy and 91% validation accuracy. In this proposed work, the multilingual text is eliminated, but in the feature, those multilingual texts are converted into a common language automatically and user opinion analysis is performed to improve prediction.

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