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ENSEMBLE HYBRID MODEL FOR COVID-19 SENTIMENT ANALYSIS WITH CUCKOO SEARCH OPTIMIZATION ALGORITHM

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Abstract. The COVID-19 pandemic has caused anxiety and fear worldwide, affecting people's physical and mental health. This research work proposes a sentiment analysis approach to better understand the public's perception of COVID-19 in India. Two datasets are created by collecting tweets regarding COVID-19 in India. Pre-processing and analysis of datasets are performed by using natural language processing (NLP) techniques. Various features are extracted from collected tweets using three-word embeddings GloVe, fastText, Elmo. The optimal features are selected by cuckoo search optimization algorithm. Finally, the proposed hybrid model of Gated Recurrent Unit (GRU) and Bidirectional Long Short-Term Memory (BiLSTM) is used to categorize the tweets into three sentiment categories. Proposed model achieved 94.44% accuracy, 90.34% precision, 88.53% sensitivity, and 89.53% F1 score. It significantly improved over previous approaches, which achieved 80% accuracy.

Key words: COVID-19, Sentiment, Cuckoo Search, Optimization, Deep learning, Ensemble learning

1. Introduction. COVID-19, or Coronavirus disease, is a virus that infected millions of people and puts human lives at risk worldwide [47]. It is a highly contagious virus that spreads quickly and causes serious illnesses, including death. World health organization (WHO) declared COVID-19 as pandemic due to its risk and hazards [12]. 37,109,851 COVID-19 cases and 1,070,355 fatalities have been reported by the WHO [43]. Coronavirus is a highly infectious virus that spreads among the people through sneezing, coughing, or talking [10, 23]. In addition, it can be transmitted through air droplets from an infected person. Therefore, it is important to take precautions to prevent the spread of the virus. Worldwide population are affected directly or indirectly by this crisis [5]. Sentiment analysis is one of the way to deal with this crises [20]. It is essential to understand the mindset, feelings, and fears of people to fight with this disease. Social media platform is now an integral part of our daily life to communicate and share information. The messages and tweets posted on social networking sites play an important role to understand the feelings of people. People expect accurate and reliable information about corona cases. It is analyzed that many social media posts and tweets misled the readers by publishing erroneous statistics of COVID-19 cases. However, various practices such as social distancing, wearing masks, and washing hands are some of the key measures to prevent the spread of the virus. Governments around the world have put in place measures to combat the virus, including lockdowns, travel restrictions, and other measures [17]. Many countries have started vaccination campaigns to safeguard their populations from the fatal COVID-19 disease. A vaccine is an effective way to prevent the spread of the virus, but due to shortages and access restrictions, not everyone can get it [25]. People still need to practice good hygiene and take other precautions to protect themselves and others. However, many people are hesitant to take the vaccine because of misinformation regarding its safety and effectiveness. It is important to educate people for importance of vaccination to reduce the spread of virus. The various emotional outburst tendencies of Indians can be seen on Twitter regarding COVID-19 [19]. Analyzing the mental emotions of people during epidemic periods assists the government to review previous policies and making new standards. During this epidemic, the government should make efforts to stimulate the public and restore their physical and emotional health. This research analyses the feelings of Indian tweet users about COVID-19. India has the second largest population with diverse geography in the world [24]. In order to conduct this study, several tweets are gathered from various COVID-19-related hashtags. Additionally, emotions associated with tweets are identified as WordCloud.

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Sentiment analysis can provide insights to governments and healthcare organizations to better craft strategies and policies to fight the virus. It can also help to provide psychological and emotional support to people affected by the virus. Additionally, it can provide valuable data to help researchers to develop better treatments and vaccines. Lastly, this study provides valuable insights for governments and healthcare organizations to better assess the mental health of the public during an epidemic period in order to build better policies to combat COVID-19.

1.1. Motivation. Understanding of Indians emotions about the coronavirus on social media platforms plays an important role for the government to control, monitor, and get rid of COVID-19. Significant research has not been done on the sentiment analysis of Indians towards COVID-19. In this study, sentiment analysis is conducted in order to comprehend Indian people's attitudes toward COVID-19. The findings of this study can also assist public health officials to connect effectively with individuals and provide public health solutions to the affected people.

1.2. The main contributions of this research work are as follows.

- Two annotated COVID-19 datasets are created using Twitter text for sentiment analysis.
- Various natural language processing (NLP) preprocessing techniques are employed on the collected real-time Twitter datasets, such as data cleaning, tokenization, and labelling.
- Three embedding techniques, namely ELMo, GloVe, and FastText embeddings, are used for feature extraction.
- Optimal features are selected using the Cuckoo search optimization algorithm.
- Proposed hybrid model of GRU and BiLSTM is used to determine the sentiments of Indian citizens. The results obtained from the model are compared with the performance of individual GRU, BiLSTM and existing work.
- The efficiency of the proposed model is evaluated using the F1-score, precision, accuracy, recall, and ROC.

1.3. Organization of the paper. The structure of the remaining paper is as follows: Literature review is covered in Section 2. Section 3 presents the recommended procedure. Results obtained from the suggested model are examined in Section 4, and then final conclusion is presented in Section 5.

2. Literature review. Several researchers have analyzed the people emotion regarding the COVID-19 during the lockdown and pandemic period. Many authors have used wide variety of machine learning and word embedding methods to decipher the public feeling throughout the COVID-19 period

A web portal based on real-time tweet is proposed by Venigalla et al. to reflect the Indian sentiment during COVID-19 [40]. This platform allows visitors to check general sentiment of people of specific state on specific date and time.

Limitation: of this study is that the current portal shows the state-level sentiment of few cities only.

Chakraborty et al. have been suggested a model to analyze the two types of pandemic tweets [10]. In the first scenario, 23,000 tweets from 1 Jan 2019 to 23 Mar 2020 are evaluated [1]. According to their finding, majority of tweets expressed either negative or neutral sentiments. As in the second scenario, 226,668 tweets have been analyzed with positive or neutral sentiments and achieved 81% validation accuracy. An emotion care strategy to analyse COVID-19 tweets is developed by Gupta et al. [18]. In this approach, initially, all tweets are converted into lowercase strings. All special characters, punctuation, links and retweets are effectively removed. The frequency-inverse document is utilized for the vectorization process after data cleaning. Lastly, sentiments are categorised as trust, surprise, grief, pleasure, fear, disgust, anger, and anticipation in their work. Borah et al. employed a multi-modal deep learning approach to analyze 36,231,457 tweets related to COVID-19 vaccine from 51,682 Indians [8]. All Tweets are collected using #ReadyToVaccinate, #Covishield, #CovidVaccine, and #Covaxin hashtags. Analysis is done by using SentriStrength tools which assigns a value between -4 to +4 to each tweet. Extreme negative and extreme positive sentiment is denoted by -4 and +4, respectively. The textual data and the network topology are encoded by using BERT and GraphBERT.

Limitation: Sentiment analysis is applied only to tweets posted by urban residents. The perspective of rural residents is not included in the analysis. Furthermore, only limited hashtags are used to determine inclusion of tweets in the dataset for analysis.

Kumar et al. applied hybrid model of BiLSTM and convolution neural network (CNN) to evaluate the publicly accessible Sentiment140 dataset with labelled Indian COVID-19 tweets and achieved 90% accuracy [29].

Limitation: Authors have used English text only for the sentiment analysis. The text from other languages can also be used to improve its correctness.

Misra et al. examined and acquired information regarding reverse migration in India via Twitter mining [34]. They retrieved almost 50,000 tweets from March 2021 to May 2020 by using trending hashtag such as #IndianMigrantWorkers and Twitter API. Different types of emotions are identified by using the NRC Emotion Lexicon after noise removal from collected data.

Limitation: To obtain Twitter data, the researchers exclusively used only the popular hashtags #IndianMigrantWorker and #MigrantWorker which does not reflect the entire population. The tweets posted in other languages are not included for analysis. Different perspective can be analyzed by using tweets posted in other Indian languages also.

Majumder et al. analyzed the sentiments of Indian users tweets about COVID-19 from March 2020 to June 2020 [31]. They have used supervised machine learning-based support vector machine and Logistic Regression for sentiment analysis with accuracy rates of 91.50 % and 87.75%, respectively. Chehal et al. evaluated sentiments of Indian Twitter users about online shopping during lockdown periods [11, 3]. Their analysis indicated the variations of feelings during different lockdown stages. during lockdown 2, people stocked fitness, sports, games, toys, and beauty products. While during lockdown 3, people stocked domestic goods, clothes, and nutrition products. Imran et al. evaluated feelings of people about the COVID-19 lockdown period [22]. LSTM model with FastText embedding is utilized in their research to identify the polarity of emotions with 82% accuracy. Chintalpudi et al. collected posts from Indian Twitter users between 23 March and 15 July 2020 for sentiment analysis [14]. Authors utilized the BERT [39] method for the text analysis and obtained an accuracy of 89%.

Basiri et al. suggested a new approach for coronavirus-related tweet emotion categorization by combining four deep learning methods : DistilBERT [27], fast text, BiGRU, and CNN [6]. Large labelled dataset of tweets is used to train the classification models and achieved highest 85.5% accuracy. Bhat et al. analysed the worldwide attitude expressed on Twitter [7]. Total 92,646 and 85,513 tweets related to #COVID-19 and #Coronavirus are collected, respectively. They have obtained 13.96%, 34.05%, and 51.97% of the tweets as negative, neutral, and positive attitudes for #COVID-19 sentiment study [2]. The authors obtained 41.27%, 40.91%, and 17.80% of neutral, positive and negative tweets, respectively for sentiment analysis of coronavirus. Only a few research work is done for sentiment analysis of Indians based on COVID-19 tweets. In this work, integration of metaheuristic optimization based cuckoo search algorithm with hybrid deep learning model of GRU and LSTM is applied for sentiment analysis and classification of Indians COVID-19 tweets.

List of abbreviations used in this paper is provided in table 2.1. Summary of the literature review is shown in table 2.2.

3. Proposed framework. The proposed framework for sentiment analysis is broadly divided into three steps as: (1) Data collection, (ii) Data preprocessing, and, (iii) Evaluation of emotional states. Flowchart of suggested framework is depicted in Fig 3.1. Following sub-sections provide a brief summary of each stage.

3.1. Data collection. Tweets collected from the Twitter platform are utilized in this work to examine the Indian sentiments during pandemic. Various terms such as #COVID-19, #COVIDindia, #coronavirusinindia, #coronaindia, #lockdownindia, #coronavirusindia, #staysafe, #stayhome, #indiafightscorona, and #coronavirus are used for filtration of Twitter posts. Number of collected tweets by using different hashtags are shown in Table 3.1. Two datasets of geo-tagged tweets are constructed from January to March 2021 and December to May 2022 by applying Python's Twint package.

3.2. Data pre-processing. It is used to perform various task given as: (i) data cleaning, (ii) tokenization, (iii) data normalization, (iv) data labelling and feature extraction, and (iv) feature selection. The following subsections provide a brief summary of each step.

Table 2.1: Name of Abbreviation and its full form.

Abbreviation	Full Form
NLP	Natural Language Processing
GRU	Gated Recurrent Unit
BiLSTM	Bidirectional Long Short-Term Memory
WHO	World health organization
ROC	Receiver operating characteristic curve
BiGRU	Bidirectional GRU
CNN	Convolutional neural network
LSTM	Long short-term memory
VADER	Valence Aware Dictionary for Sentiment Reasoning
GloVe	Global vectors
ELMo	Embeddings from Language Models
CS	Cuckoo search
MAD	Mean absolute difference
BiLSTM	Bidirectional LSTM
SVM	Support Vector Machine
BERT	Bidirectional Encoder Representations from Transformers

Table 2.2: Summary of the literature review

Reference	Approach/Model
Chakraborty et al. [10]	deep learning based model
Majumder et al. [31]	SVM and Logistic Regression
Imran et al. [22]	LSTM+FastText
Chintalapudi et al. [14]	BERT
Basiri et al. [6]	Fusion-based

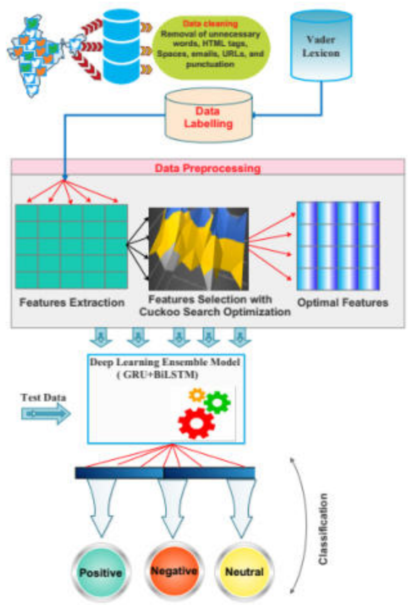


Fig. 3.1: Overview of proposed framework

Table 3.1: The number of Hashtags utilized for collecting the tweets.

Twitter hashtags	Number of tweets
#coronavirus	16,803
#indiafightscorona	14,705
#stayhome	16,106
#staysafe	18,117
#lockdownindia	20,501
#coronaindia	16,476
#covid19	17,295

Table 3.2: Count of labelled tweets by VADER technique

	DATA_SET 1	DATA_SET 1
Number of tweets in the dataset	1,200,000	1,500,000
Number of tweets containing emotion	1,200,000	1,500,000
Positive Twitter post	285,240	318,900
Negative Twitter post	436,080	530,100
Neutral Twitter post	478,680	651,000

i. **Data cleaning**

Original tweets collected from social media contain unwanted data. Data cleaning is used for removal of various unused terms such as: (a) spaces, emails, URLs, (b) additional characters in sentences, (c) punctuation (d) HTML tags, (e) unnecessary words and emojis from collected data. This step is carried out by using regular expressions.

ii. **Tokenization**

Primary purpose of this step is to determine the words or groups of words in a phrase which serves as the foundation for text analysis. In this process, entire text is broken down into smaller and more manageable chunks termed as "tokens" [41]. The meaningful analysis of text is mainly based on the tokens rather than the entire text. Sample example of text and extracted tokens by tokenization process is given as:

iii. **Example Text** "Our industry was almost destroyed by covid wear a mask". **Extracted token set**: {'Our', 'industry', 'was', 'almost', 'destroyed', 'by', 'covid', 'wear', 'a', mask'}.

iv. **Normalization**

This step considerably reduces the amount of data and improves the computing performance of algorithm [42]. This process converts all extracted tokens into a standard form that can be used to find similar-sounding words and eliminates the offending ones. In this work, three text normalization techniques namely, Lower-casing, stemming, and lemmatization are applied. All upper-case letters are converted into lower-case by Lower-casing. Stemming is used to remove all prefixes and suffixes from a phrase and return its basic structure. Lemmatization is employed to reduce dimensionality by classifying synonyms together.

v. **Data labelling**

In this work, lexicon approach based data labelling process known as VADER is applied to determine the polarity of tweets [35]. Each tweet is labelled as positive, negative, or neutral based on VADER compound score. Positive label is assigned to all data having greater than or equal to 0.05 compound score [21]. All data with scores between -0.05 and +0.05, less than -0.05 is assigned as neutral, and negative, respectively [21, 44]. Count of tweets labelled as positive, negative, and neutral by VADER technique is shown in Table 3.2.

3.2.1. Feature extraction. Further, all features are extracted by applying three embedding techniques: GloVe, FastText, and Elmo. This step minimizes memory needs and speeds up the processing of subsequent data.

- **FastText**
  FastText word embedding technique is a free, open-source package for text representations and classification [26]. It allows the framework to build a model quickly. This technique provides embedding of misspelled, unusual, and untrained words [33]. Numerous terms of dataset can not be embedded with FastText technique. It is also analyzed from the experiment that FastText technique missed 7,591 words from dataset for word embeddings. To overcome the limitation of FastText, Genism FastText algorithm is used to determine word vectors by using following equation:

$$\mu_s = \frac{1}{W}\sum_{q=1}^{W} d_q \log\left(r\left(MSa_q\right)\right) \tag{3.1}$$

  In this context, μ_s represents the cumulative log-likelihood, a_q is a one-hot-encoded word, S denotes lookup matrix used to find the word embedding in W documents [13], M represents continuous output transformation, softmax function is denoted by r.
- **Glove**
  Global Vectors (Glove) is an unsupervised learning technique used to construct low-dimensional word distributed representation [30]. It reduces dimension of word-context matrices by keeping track of word pair co-occurrences of corpus. It presents an attenuation function to compute weight based on distance between two words of context window [16].
- **ELMo**
  This technique is based on character and word-level context embedding [37]. It considers complete sentence while determining the appropriate embedding for each word. It uses bi-directional recurrent neural network to generate embeddings. The bidirectional embedding technique depends on both proceeding and succeeding word of sentence [48]. ELMo contextualizes each token by concatenating BiLSTM states.

3.3. Feature selection. Cuckoo search (CS) algorithm is used to select optimal features [46]. It is based on natural-inspired metaheuristic optimization approach and belongs to swarm intelligence family. Detailed description of fitness function and CS algorithm is given in next subsections.

3.3.1. Fitness function. Mean absolute difference (MAD) is used as the fitness function in this study to evaluate the significance of individual words. It accepts a ***weight_matrix*** as input, updates the weights of each word in the matrix depending on its fitness value, and generates a new ***updated_weight_matrix***. Fitness function determines the relevance of word depending on its weight. MAD calculates text's significance by comparing its mean value to mathematical phrase and it is given as follows:

$$MAD(Xh_m) = \frac{1}{Xh_m}\sum_{p=1}^{n} \mid r_m, p - \overline{r_b} \mid \tag{3.2}$$

$$\overline{r_b} = \frac{1}{Xh_m}\sum_{P=1}^{n} r_{m,P} \tag{3.3}$$

Here, Xh_m represents total number of text characteristics derived from sentence X. Average value of vector m is represented by r_m. $\overline{r_b}$ represents weight value of feature P in the text and n represents total number of text characteristics in original data set.

3.3.2. Cuckoo search algorithm. This user-friendly algorithm adheres the following basic principles [32]:
i. Cuckoo placed its egg in an arbitrary nest.
ii. The ideal nest produces high-quality eggs that carried down to the next generation.

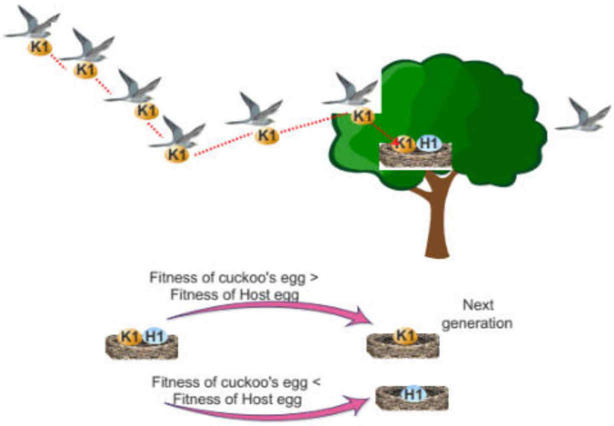


Fig. 3.2: Behaviour of cuckoo birds

iii. Chance of discovering cuckoo eggs by the host birds is Pa [0, 1] [45]. As soon as the host bird detects an alien egg, it can either (i) discard the eggs, or (ii) abandon the nest and build another one. Figure 3.2 depicts the behaviour and features of cuckoo birds.

Updated_weight_matrix is given as the initial population to the cuckoo search algorithm for optimal feature selection. It uses both local and global random walks to explore the search space [15]. Egg values are continuously updated using local random walk. Levy Flight algorithm is used to implement the global random walk [4]. Levy arrangement is used by this algorithm to determine stride length. The CS algorithm can efficiently probe the search space due to steady increment of step size [36]. Steps of Cuckoo search algorithm is presented in Algorithm 1.

Algorithm 1 Cuckoo Search Algorithm

1. Initialization of population for M nests, probability $Q_y \in [0,1]$ and maximum maximum iterations $\{A\}$.
2. Set m= 0.
3. ***for*** (p = 1, p <= M) **do**
4. Take population $z_p(m)$ for host M.
5. Determine the fitness value of $h(z_p(m))$.
6. ***end for***
7. Make a new $z_{p+1}(m)$ solution randomly by Levy flight.
8. Determine the fitness value $h(z_p(m+1))$ for $z_{p+1}(m)$.
9. Randomly select a nest z_q from M
10. ***if*** $h(z_p(m+1)) > h(z_q(m)$ **then**
11. Substitute $(z_p(m+1)$ in-place of $(z_q(m+1))$.
12. ***end if***
13. Based on the Q_y value, the worst nests are discarded.
14. Replace the old ones nest with Levy flight.
15. Consider the finest options.
16. Sort the solutions and choose the best one.
17. increase the iteration counter $m = m + 1$.
18. Repeat step 7 to 17 until $m < A$.
19. Get the optimal solution.

Table 3.3: Parameter values initialized for cuckoo search

Parameter	Value
Probability (P_a)	0.25
Step scaling factor α	2
Number of iterations	765
σ_v	1
σ_μ	1.5

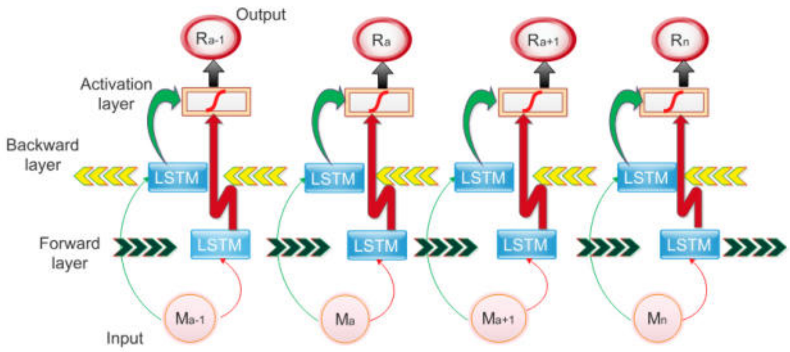


Fig. 3.3: Architecture of BiLSTM model

A new solution $z_p(m+1)$ for the cuckoo p is generated by the equation given as:

$$z_p(m+1) = z_p(m) + \alpha \oplus \text{Levy}(\lambda) \tag{3.4}$$

In this case, value of the current generation is represented by $m \in 1, 2, ..., A$, while A represents the maximum number of iterations. α denotes Levy flight with step length of 2 for the best search pattern with randomly placed objects [9]. Entry-wise multiplications are represented by $\oplus$. Random walk obtained with Levy distribution step is represented by the equation given as:

$$\text{Levy } = 0.01 \times \frac{\mu}{|v|^{1/\beta}} \times (g_{\text{best }} - z_p m)) \tag{3.5}$$

where μ =1.5 and v=1 denotes the normally distributed values, and g_{best} represents the current global best nest.

The cuckoo search technique returns an optimised weight matrix which is given as input to the classification model. List of parameter values set for cuckoo search algorithm is shown in Table 3.3.

3.4. Classification model.

i. **BiLSTM Model**

This work uses a variant of the LSTM network known as Bidirectional LSTM (BiLSTM) for sentiment classification. LSTM performs well with variable-length sequences but it cannot exploit contextual information from future tokens [38]. While BiLSTM combines past and future inputs of particular time step into LSTM model. BiLSTM employs a bidirectional LSTM layer to discover the patterns by traversing input data history into both directions. The first layer processed the forward sequence, while the backward sequence is handled by the second layer [28]. Figure 3.3 depicts the structure of BiLSTM model.

ii. **Gated Recurrent Unit Model (GRU)**

Architecture of this model is quite comparable with LSTM approach. It has its own dedicated memory

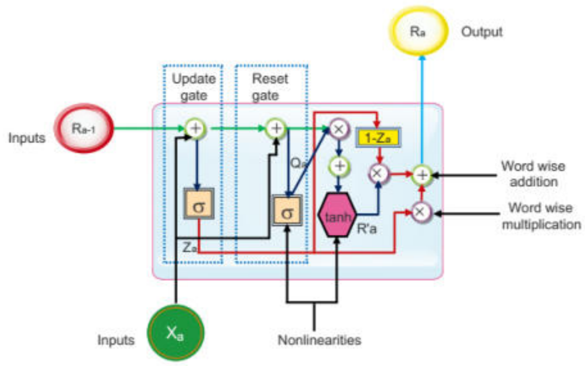


Fig. 3.4: Architecture of GRU model

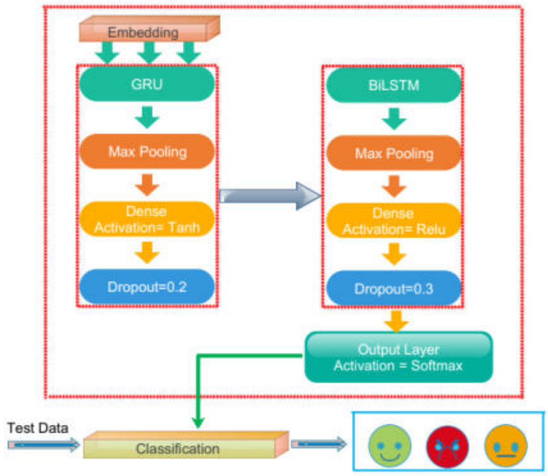


Fig. 3.5: Architecture of proposed model

and gating mechanism for controlling data transfer inside the unit. GRU uses two gates, (i) update and (ii) reset, to control the amount of information transferred or rejected from the preceding levels. Figure 3.4 presents the architecture of this model.

iii. **GRU-BiLSTM model**

It is a hybrid model of both GRU and BiLSTM approaches. First step is to feed the word embedding vector into GRU model with hidden layer. GRU layer transfers its output into dense layer of BiLSTM unit. Dropout layer is followed by dense network. Finally, sentiment classes are classified using softmax activation function. Hybrid model of the GRU- BiLSTM is shown in Figure 3.5.

4. Experiment and result. Quantitative sentiment analysis of COVID-19 tweets of Indian users are evaluated. The proposed work uses NVIDIA P2200 display card, 32 GB RAM with i8 E-2236 processor, and Python 3.7 language. Experimental results of sentiment analysis are discussed in the next subsections.

4.1. Results of sentiment analysis. Sentiment distribution of COVID-19 tweets of both datasets is shown in Figure 4.1. Tweets of first dataset are analyzed as 285,240 positive, 436,080 negatives, and 478,680

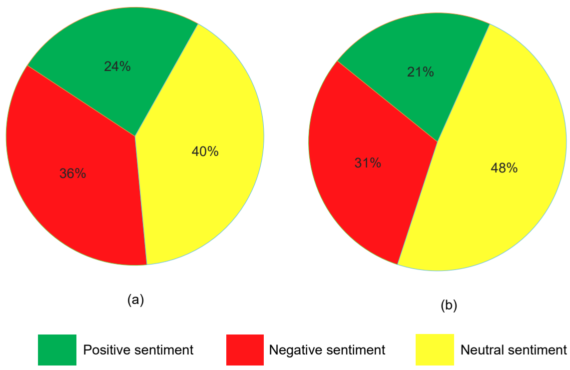


Fig. 4.1: Sentiment distribution of datasets

neutral tweets. For the second data set, 318,900, 530,100, and 651,000 tweets are categorized as favorable, negative, and neutral, respectively.

4.2. Classification results and discussion. Proposed model is used to classify sentiment of COVID-19 related tweets. Classification output is obtained by applying three models namely, (a) GRU, (b) BiLSTM, and (c) GRU+BiLSTM.
Various metrics such as F1-score, recall, precision, and accuracy are used to evaluate classifier performance, Description of each of these parameters are given as:

$$Accuracy = \frac{\sum(S\_F, S\_R)}{\sum(S\_F, U\_F, S\_R, U\_R)} \tag{4.1}$$

Specifically, S_F, S_R, U_F, and U_R denote correct identification, wrong identification, correct rejection, and wrong rejection.

$$Precision = \frac{(S\_F)}{\sum(S\_F, U\_F)} \tag{4.2}$$

$$Recall = \frac{(S\_F)}{\sum(S\_R, U\_R)} \tag{4.3}$$

$$F1 - score = \frac{2 * (Recall * Precision)}{\sum(Recall, Precision)} \tag{4.4}$$

The various parameter values taken for hybrid deep learning model are shown in table 4.1. Set of optimal parameter values are used to calibrate the experimental models. Dimension of embedding layer is initialized as 400. Suggested model uses hidden layer with 128 neurons and dropout layer with 0.7. Learning rate followed with Adam optimizer is set as 0.001. Softmax function is used to optimize output layer.

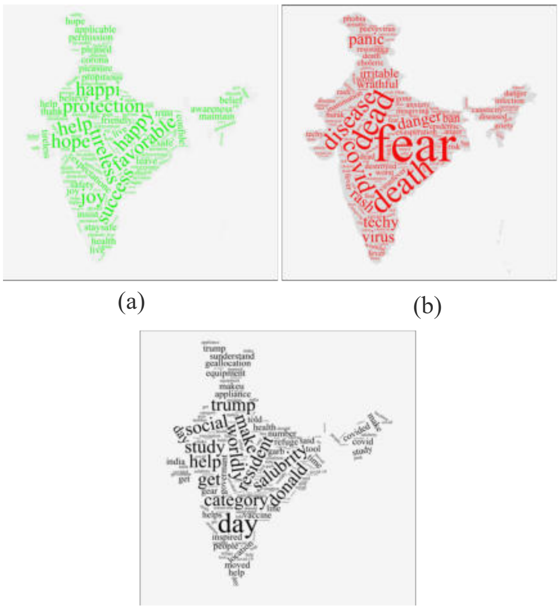
4.3. Comparison with Existing Model. The classifiers performance of Twitter sentiment analysis about COVID-19 with extracted features by using FastText, Glove, Elmo embedding method, and selected features with CS algorithm are shown in Table 4.2. It is analyzed from table 4.2 that the hybrid classifier gives improved values with selected features. Proposed model obtains the highest 94.44%, 88.53%, 90.34%, and 89.77% accuracy, sensitivity, precision, and F1-score.

WordCloud modules of words related to negative, positive, and neutral sentiment are visualized in Figure 4.2 (a), (b), and (c), respectively.

Table 4.3 shows performance comparison of proposed model with results obtained by existing authors.

Table 4.1: Different parameter values initialized for classifiers

Parameter name	**GRU**	**BiLSTM**	**GRU+BiLSTM**
Epoch	115	112	93
Batch size	32	64	64
Optimizer	Adam	Adam	Adam
Pooling layer padding	Same	Same	Same
Size of Max-pooling layer	2	2	2
Activation function	SGD	Relu	Relu
Filters	32	64	64
Kernel size	3	3	5
Dense layer	44	64	128
Momentum	0.7	0.7	0.7
Dropout layer	0.2	0.3	0.3
Model Learning rate	0.001	0.001	0.001



(a) (b)

(a)

Fig. 4.2: Most frequently words used as negative, positive, and neutral.

For sentiment classification, Chakraborty et al. [10] analyzed 249658 unique tweets by using deep learning-based model and achieved 81% accuracy. Majumder et al. [31] utilized SVM classifier and Logistic Regression to analyze COVID-19 Indian sentiments between March to June 2020. They have obtained 91.50% and 87.75% accuracy with SVM and Logistic Regression, respectively. Imran et al.[22] applied Long short-term memory model to extract sentiment polarity and emotions from tweets. They have obtained accuracy of 82% on sentiment140 dataset with FastText embedding.

Chintalapudi et al. [14] analyses Indian tweets using BERT model and achieved 89% accuracy. Basiri et al. [6] analyzed coronavirus-related tweets from eight countries and obtained 85.5% accuracy. Highest 94.44% accuracy is achieved by the proposed model which is higher than the results obtained with existing techniques [10, 31, 22, 14, 6].

Table 4.2: Results obtained with the various deep learning classifiers

Embedding	Model	Precision	F-score	Sensitivity	Accuracy
FastText	BiLSTM	71.82%	71.71%	72.16%	76.35%
	GRU	76.36%	71.49%	72.69%	78.21%
	GRU+BiLSTM	75.74%	73.40%	79.74%	79.32%
Glove	BiLSTM	78.83%	81.38%	79.87%	79.54%
	GRU	74.27%	80.41%	81.49%	82.74%
	GRU+BiLSTM	81.21%	79.70%	84.78%	85.11%
ELMo	BiLSTM	81.33%	84.63%	82.14%	80.54%
	GRU	79.27%	75.41%	80.17%	84.12%
	GRU+BiLSTM	84.19%	82.14%	79.69%	85.64%
ELMo+CS	BiLSTM	85.73%	84.37%	86.41%	85.54%
	GRU	90.77%	88.31%	86.49%	91.42%
	GRU+BiLSTM	90.34%	89.77%	88.53%	94.44%

Table 4.3: Comparison of the suggested model with existing work

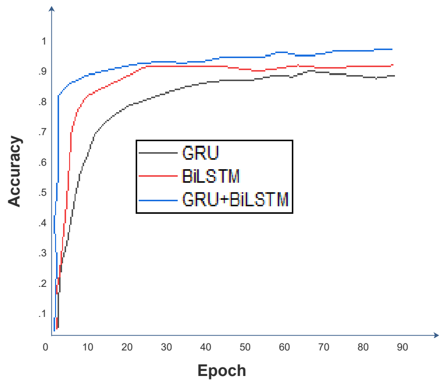
Reference	Approach/Model	Accuracy
Chakraborty et al. [10]	deep learning based model	81%
Majumder et al. [31]	SVM and Logistic Regression	91.50% and 87.75%
Imran et al. [22]	LSTM+FastText	82%
Chintalapudi et al. [14]	BERT	89%
Basiri et al. [6]	Fusion-based	85.5%
Propose model	GRU+BiLSTM	94.44%

Training accuracy and training loss obtained by GRU, LSTM, and hybrid model are illustrated in Figures 4.3 (a) and 4.3(b), respectively. Validation accuracy and loss are depicted in Figures 4.4 (a) and 4.4 (b), respectively. It is observed from Figures 4.3(a) and 4.4(a) that the classification accuracy of the proposed hybrid model is more significant as compare to individual GRU and LSTM models for maximum epochs. Furthermore, Figures 4.3 (b) and 4.4 (b) shows that hybrid model gives lower loss value as compare to other deep learning models. Confusion matrix of suggested model is depicted in Figure 4.5 (a). Mis-classification occurs when positive and negative samples are wrongly classified as neutral, while neutral emotion is incorrectly identified as negative.

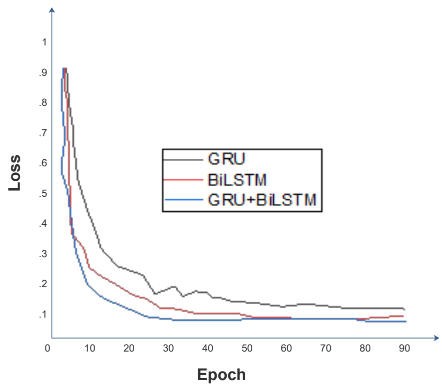
According to obtained confusion matrix, neutral feelings are more prevalent than positive and negative sentiments. Furthermore, comparison between the proposed and traditional deep learning model based on ROC and AUC measurement is shown in Figure 4.5 (b). Higher AUC indicates better model categorization. It is analyzed that the proposed model consistently outperformed with AUC of 0.97. Accuracy acquired by suggested model is shown as a boxplot also in Figure 4.6. It signifies consistent performance of the suggested model.

5. Conclusions. The proposed framework for sentiment analysis of Indians towards coronavirus using Twitter data achieved state-of-the-art performance. Proposed hybrid model of GRU and LSTM classification model outperformed individual and existing machine-learning techniques for COVID-19 emotion classification. The proposed model achieved a precision, F-score, sensitivity, and accuracy of 90.34%, 89.77%, 88.53%, and 94.44%, respectively. This is a significant improvement over previous approaches, which typically achieved 80% accuracy. The suggested hybrid model with enhanced word vector space improves the accuracy.

Results obtained from this research work can be used by policymakers and healthcare administrators to better understand the impact of COVID-19 on Indian society. The framework can also be used to monitor public sentiment about COVID-19 and to identify emerging trends. In future, proposed framework can be improved by adding part-of-speech annotations with individual words in the corpus. This will allow the framework to better understand the meaning of words and to achieve even higher accuracy. Additionally, proposed framework



(a)



(b)

Fig. 4.3: Training accuracy (a), Training loss (b) with respect to epochs

can be used to analyze vaccine-related tweets posted by Indian users. This will help to better understand the public sentiment about vaccines and to identify potential vaccine uptake challenges.

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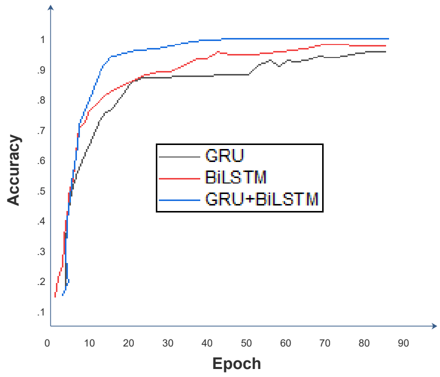
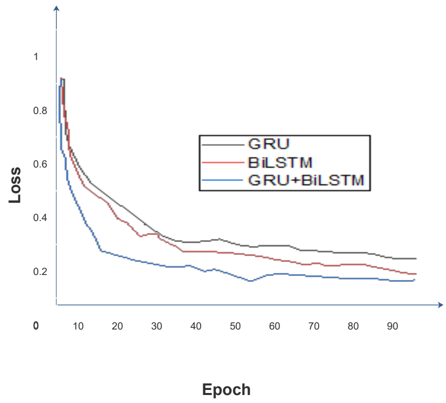


(a)



(b)

Fig. 4.4: Validation accuracy (a), Validation (b) with respect to epochs

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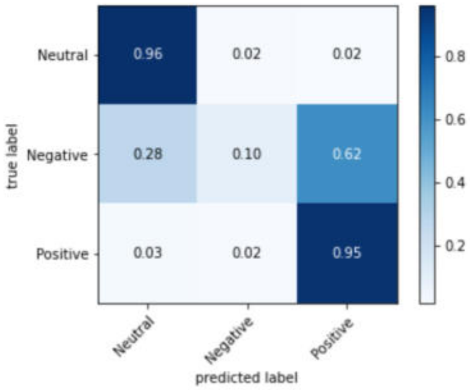
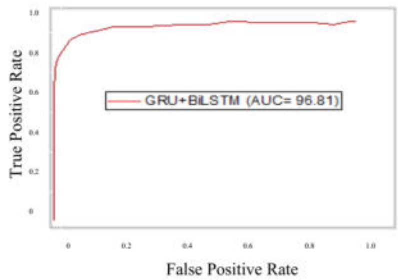


(a)



(b)

Fig. 4.5: Confusion matrix (a), ROC curve (b) with of proposed model

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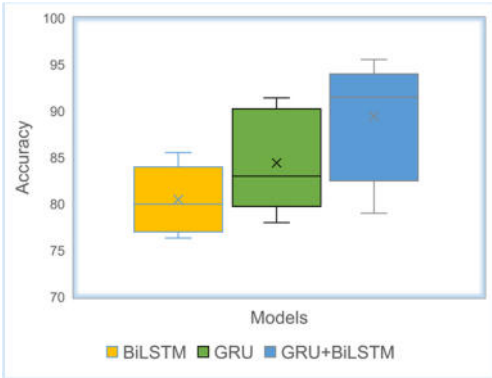

Fig. 4.6: Boxplot accuracy of proposed model

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