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Recurrent neural network based sentiment analysis of social media data during corona pandemic under national lockdown

Shana Jayachandran[a,1,*] and Anveshini Dumala[b]
[a]*Department of Computer Applications, Coimbatore Institute of Technology, Coimbatore, Tamilnadu, India*
[b]*Department of Information Technology, Vignan's Nirula Institute of Technology and Science for Women, Guntur, India*

Abstract. The Corona virus pandemic has affected the normal course of life. People all over the world take the social media to express their opinions and general emotions regarding this phenomenon. In a relatively short period of time, tweets about the new Corona virus increased by an amount never before seen on the social networking site Twitter. In this research work, Sentiment Analysis of Social Media Data to Identify the Feelings of Indians during Corona Pandemic under National Lockdown using recurrent neural network is proposed. The proposed method is analyzed using four steps: that is Data collection, data preparation, Building sentiment analysis model and Visualization of the results. For Data collection, the twitter dataset are collected from social networking platform twitter by application programming interface. For Data preparation, the input data set are pre-processed for removing URL links, removing unnecessary spaces, removing punctuations and numbers. After data cleaning or preprocessing entire particular characters and non-US characters from Standard Code for Information Interchange, apart from hash tag, are extracted as refined tweet text. In addition, entire behaviors less than three alphabets are not assumed at analysis of tweets, lastly, tokenization and derivation was carried out by Porter Stemmer to perform opinion mining. To authenticate the method, categorized the tweets linked to COVID-19 national lockdown. For categorization, recurrent neural method is used. RNN classify the sentiment classification as positive, negative and neutral sentiment scores. The efficiency of the proposed RNN based Sentimental analysis classification of COVID-19 is assessed various performances by evaluation metrics, like sensitivity, precision, recall, f-measure, specificity and accuracy. The proposed method attains 24.51%, 25.35%, 31.45% and 24.53% high accuracy, 43.51%, 52.35%, 21.45% and 28.53% high sensitivity than the existing methods.

Keywords: COVID 19, sentiment analysis, data analytics, lockdown, classification, recurrent neural network

1. Introduction

In 2019, COVID 19 viral disease was formed; a number of patients infected from a wet seafood market at Wuhan, China. Then the infected patients are isolated and molecular analysis on pathogen is the novel corona virus (CoV) initially called 2019-nCoV, later WHO changed the name of this disease to COVID 19. Then the viruses have been spread all over the world, with almost every country fighting the virus and doing everything possible to reduce the spread of the virus as soon as possible. World Health Organization has announced as pandemic and they suggested vaccine engaged in the work of preparation. There are many academic studies that may guide researchers for learning the impact of pandemic on people's mental health and on the world wide economie [1].

[1]ORCID ID: 0000-0001-5019-1077
*Corresponding author. Shana Jayachandran, Associate Professor, Department of Computer Applications, Coimbatore Institute of Technology, Coimbatore, Tamilnadu, India. E-mail: shana.cta@gmail.com.

In the first week of March 2020, various countries such as China, Italy, Spain, Australia were fighting the COVID 19 pandemic via carrying severe measures, such as national blockade and containing the area where the risk of community spread was suspected. By consulting foreign counterparts, Indian government made a major national lockdown decision on March 25 for 21 days from March 26 to April 14, 2020. To control the virus spread it was extended until May 3 2020, it was known as lockdown 2.0. With easy curbs, until May 17, 2020 was known as lockdown 3.0. The next lockdown was launched on May 31, 2020, known as lockdown 4.0,the country was divided as zones, viz red, orange, green [2].

In India, the primary case was identified at Jan 30, 2020 in the state of Kerala. Outbreaks in India are categorized from the case group using the World Health Organization's data report. Original source of transmission was linked to wholesale seafood market in China with bats being assumed the primary host of dangerous virus; while pigs or pangolins are considered as intermediary hosts [3, 4] Maximum number of infections in humans led to transmission theories as animals to humans. Chalked routes of transmission so far contain direct contact, fomite transmission, respiratory droplets, and faucal-oral transmission. Symptoms for fever, dry cough, diarrhea, nausea, giddiness, and abdomen pain are signs of infection virus [5–7].

India is essential for analyzing the spread as well as effect of corona virus in India. The micro-blogging website Twitter is used for analyzing the feelings of people of India. Though, feeling of Indians during the initial lockdown is often favored by few events such as hatred, anger and sadness [8–10]. It is necessary for the government to record the sentiment from time to time to take an essential action. Such actions or events impact a person's sentiment ormental well-being. Authorities, after knowing the emotional state of the citizens, may mark beneficial policies for them. Additionally, e-commerce stakeholders may adjust based on its status and regulates supply and demand for products [11–13].

Nevertheless, it is negativity, fear, hatred and sadness on lockdown. Indians dependence government, also could have confidence, the government would successfully execute the curfew as well as ensure that no citizen fought for fundamentals during blockade together with necessary arrangements for it [14]. Few tweets express total surprise at this conclusion, other than in general, it seem that people expected a measure like the confinement to spread the virus, which is only possible via social distancing together with practice of hygiene measures.

Looking at COVID 19 statistics, the infection came from other countries and Indians recognize a drastic events are required in India for preventing rapid increase in numbers [15]. They use Twitter for examination. Tweets are scrutinized for measuring the feeling. Twitter sentiment analysis model is basically a classification model. The proposed method uses RNN for analysing the sentiment of people on the corona pandemic during the days of national lockdown. Tweets are removed by two prominent keywords called India Lockdown and India fights Corona from March 25 [16].

One of the rapidly developing research areas is sentiment analysis from social media data. It could play a significant role in case of medical emergencies, like COVID-19 pandemic. Several methods on sentiment classification of Social Media Data to Identify the Feelings of Indians during Corona Pandemic under National Lockdown were suggested. But the existing methods does not accurately classify the sentiment classification of twitter data also does not identify the human emotion. This can be motivated to do this research work.

The main contributions of this work are,

- Sentiment Analysis of Social Media Data to Identify the Feelings of Indians during Corona Pandemic under National Lockdown using RNN method.
- The COVID-19 tweets data set are analyzed using four steps: that is Data collection, data preparation, Building sentiment analysis model and Visualization of the results.
- For Data collection, the twitter dataset are collected from social networking platform twitter by application programming interface.
- For Data preparation, the input data set are preprocessed for removing URL links, removing unnecessary spaces, removing punctuations and numbers.
- After data cleaning or preprocessing entire particular characters and non-US characters from Standard Code for Information Interchange, apart from hash tag, are extracted as refined tweet text. In addition, entire behaviors less than three alphabets are not assumed at analysis of tweets, lastly, tokenization and derivation was carried out by Porter Stemmer to perform opinion mining.
- To authenticate the method, categorized the tweets linked to COVID-19 national lockdown.

For categorization, recurrent neural method is used. RNN classify the sentiment classification as positive, negative and neutral sentiment scores.

- The efficiency of the proposed RNN based Sentimental analysis classification of COVID-19 is assessed various performances by evaluation metrics, like sensitivity, precision, recall, f-measure, specificity and accuracy.
- Finally, the efficiency of the proposed RNN method is compared with four existing methods: sentiment analysis of COVID-19 utilizing Novel fusion-based deep learning model (FB-DL) [17], Hybrid Heterogeneous Support Vector Machine (H-SVM [18], LSTM recurrent neural network (RNN-LSTM) [19], Majority Voting technique-based Ensemble Deep Learning(MVEDL) [20].

Remaining manuscript is structured as: section 2 presents the literature review, section 3 depicts the proposed method, section 4 proves the results with discussion, section 5 concludes the manuscript.

2. Literature review

Sentimental analysis or opinion mining is a functional region of study in the field of natural language processing that analyzes individual's opinion, sentiments, assumptions, perspectives, and feelings by means of computational treatment. LIWC utilizes an exclusive word reference of nearly 4,500 words sorted out of 76 classes, remembering 905 words and divided into two classes, positive feelings and negative feelings related to sentiment analysis. Turning point emerged in the application of sentiment analysis on social media data, which is increasing number of studies by several social media platforms for acquiring the sentiment of crowds [21]. It provides minimum accuracy.

To examine general sentiments in Twitter, 2381,297 related tweets are gathered in Turkish and English language. Turkish sentiments deemed note worthy, because Turkey greeting huge count of Syrian refugees, also first carried information in Turkish tweets that reflected the general perception of the refugee hosting country. It acts the relative sense analysis of rescued tweets. The outcomes represent the Turkish tweets sentiments are substantially varied from English tweets sentiments. Here, concluded the Turkish tweets have more +ve sentiments, besides, the huge count of English tweets through substantial margin contains neutral sentiments, which is imitated by -ve sentiments. The ratio of +ve sentiments in Turkish tweets is higher (35%), the ratio of English tweets has lesser +ve sentiments towards Syrians and refugees (12%).This method does not accurately classify the sentimental analysis.

Nilima et al., [22] presented an approach to investigate the psychosocial factors linked by national closure of COVID 19 in India. Online survey was carried out on 2020 Apr 11–16, at 28 states including 8 Union Territories. Contributors have employed by snowball sample process. The cross-section online survey was carried out every state in India. The spatial analysis were done, also Moran's I statistic were utilized for exploring the entire clustering positions. The exact assessments of fisher's have been employed for examining. GeoDa with R console was deemed for assess the data. Here, get 1316 responses. Significant involvement was noted in the fact that locking operations and militant government strategy, job profile and physical activity are associated to psychosocial impact. The public health administrators assume community sentiments when planning methods related to pandemic. The presented study helps lawmakers to emphasize the psychology of people along physical condition. The major intention was to assess the psycho-social aspects related to COVID-19 and nationwide lockdown utilizing the spatial analysis. It achieves higher recall with maximum mean

Kandasamy et al., [23] presented that conceptual processing and emotional analysis would fascinate inter-disciplinary investigation. Social media network evaluation, social media absolute volume text obtainable for emotional analysis, was multiplied by many, resulting in a formidable corpus. Tweet sentiment analysis plays out for gauging public opinion on several policies, legislation, personality, social movements. In sentimental analysis of twitter data, fuzzy logic has been utilized where neutrosophy, which takes into account the perception of indeterminacy was not utilized for analyzing tweets. With the help of 2 positive, 3 intermediate and 2 negative members, the multi-refined neutrosophic set was presented. In tweets sentiment analysis such as single value neutrosophic set (SVNS), triple refined indeterminate neutrosophic set (TRINS) together with MRNS were utilized for 10 dissimilar topics. Eight of these topics were selected for emotional investigations that linked the two topics towards the Indian scene and International scene. Comparative investigation method displays, which MRNS methods gives the best refinement of current data.

Gupta et al., [24] have presented a sentiment analysis of tweets posted by Indian citizens was analyzed utilizing natural language process and machine learning (ML) classifiers. The main aim was to control Indian citizen's sentiments by nationwide lockdown implemented by the government of India to less spreading of Corona virus. Taking decisions of removal of safe zones were become dangerous for keeping the people's sentiments under control. A total of 12 741 tweets having "India lockdown" around April 5 to 17, 2020 were mined. Data was extracted from Twitter utilizing Tweepy API, annotated utilizing Text Blob along VADER lexicons, also preprocessed utilizing the natural language tool kit called Python. Research achieved 84.4% greatest accuracy including Linear SVC classifier, unigrams. The presented research states that many Indian citizens were supported the decision of lockdown which were implemented by the Indian government during the outburst of corona.

Basiri et al., [25] presented the sentiment forecast methods were frequently utilized to allocate numeric scores to free-text assess printed through people on online assess websites. To take advantage of textual content fine-grained structural information, assess can be viewed from sentence collection, everyone with their own sentimental orientation and punctuation. Thus, a method score aggregation was required for combining sentence-level scores to the general review grade. While the recent operations focus on designing effectual sentence-level forecast techniques, issue of getting well-organized algorithms of score aggregation. Based on existing technique investigation, the suggested novel scores aggregation technique in terms of Dumpster-Shafer theory of evidence. Here, initially noticed the review polarity using ML strategy as well as considering the sentence scores as a proof for general ratings of assess. Outcomes from two public data sets from the social web display the highest performance of the presented technique compared to existing techniques.

Islam et al., [26] presented COVID 19 added to mental distress around the world. COVID 19 connected to psychological troubles that reports on numerous countries, together with Bangladesh. It was a lack of studies of access to COVID 19 linked to human stress with their association through another relevant factor that affect the quality of life in country and that were investigated at current study. An online survey conducted between 340 adult populations of Bangladesh using sociodemo graphic data, probable stress of human owing to COVID 19. The dataset was analyzed during statistical tool set. Around 85.60% were participants who were in stress related to COVID 19, resulting in lack of sleep, short temper together with chaos at family. Due to COVID 19 infection, hampered programmed study plan, financial future and career uncertainty were recognized as top cases of human stress. Principal component analysis (PCA) and CA component analysis outcomes exposed a major interface between the perception of responses and human stress factors that coincided with the current scenario in the country. It was necessary to execute care tracking policy at country that can helps at management of pandemics, and nurture a positive public mental health for combating the psychological challenge related to COVID 19.

Avasthi et al., [27] have presented a sentiment analysis for gaining insight in to COVID-19 crisis. To ensure the spread of virus in minor effect, various actions and rules were taken by the government. Moreover, a major challenge was taken for monitoring the patient's mental condition. However, the basic anxiety were to keep them adjust with aspects, such as immediate changes in their daily life, rules of lockdown, entire rate of economy. Twitter, data were utilized for analyzing the topic throughout text corpus. The gathered tweet was employed for gaining the insights in the feelings of people, how they respond to actions during the situations of pandemic.

Grifoni et al., [28] have analyzed most of 17K We Ibo publications as January 13, 2020 to January 26, 2020. Analyses were depend on recognizing the psychological profile of users in terms of Online Ecological Recognition and learning models predictive automatic, and as a result recognize the user emotions. The outcome implies noticeable decrease in life fulfillment along raise in –ve feeling.

Medford et al., [29] presented that twitter was most widely utilized platforms and rich medium for analyzing various factors in population, like public sentiments, public response for situation around world, predicting disease outbreaks, etc. The posts on Twitter through January 14, 2020 and January 28, 2020 associated to Covid-19 were removed to know the feelings changes amid people about Covid-19. Tweets of negative emotions have been viewed in the shaving area at greater number of reported cases. Sharma et al., [30] have intended dashboard, which recognizes misinformation created spread regarding Covid-19, user reactions toward several emergency policy, feelings from across the country, etc., and shows them on dashboard. Taking into account, significance of posts at Twitter, Dataset was too unpredictable to give information on public response to pandemic in multiple countries along languages. Around 364,000 Twitter posts were extracted and analyzed during December 31, 2019 to February 6, 2020 to forecast the Covid-19 outbreak. It was viewed, which any tweets around the world was direct proportional to the direction of number of cases that reports on the nations. Correlations were viewed among nature of terms utilized at publications together with publications respective sentiments. They were classified in two classes: controversial and uncontroversial by LDA topic models together with analysis outcomes denoted that records by controversial words shows greater level of negative emotions through January 28, 2020 and April 9, 2020

3. Methodology

This section defines a detailed description of the proposed methodology. COVID 19 causes death, agony, chaos. For analyzing the results, few tasks are carried out. Such tasks may support to understand and extract insights from COVID 19 data, there by controlling the spread of the virus across the country. Another factor causing the virus means the impact of particular socio-economic aspects is intervened through the spreading rates of virus, which is recognize potential behaviour with socio-economic risk factors for infections and feelings, viz fear, joy, anger, sadness. They have five dissimilar tasks that were done below,

1. Forecast the corona virus spread in the region.
2. To analyze the development rates and mitigation types in the countries.
3. Forecast the epidemic will end.
4. To analyze the virus transmission rate.
5. Correlate corona virus and weather conditions [31].

Lockdown 2.0 period is noticeable by event trends like AarogyaSetu app usage, challenge of wearing your mask and motivational song of well-known Indian personalities, mass gatherings of spiritual purposes, seasoning country's corona virus warriors, such as policemen, doctors, and health personnel, and special trains facilitation for transition of trapped workers locked up to its places of origin. A total of 29,554 lockdown 2.0 tweets are collected as social networking platform twitter by application programming interfaces (APIs). A 47,672 tweets are together to 3rd block with analysis by "syuzhet" package at penny of emotions, called positive and digest. The flow process to get such sentiments and feelings is displays at Fig. 1 [32].

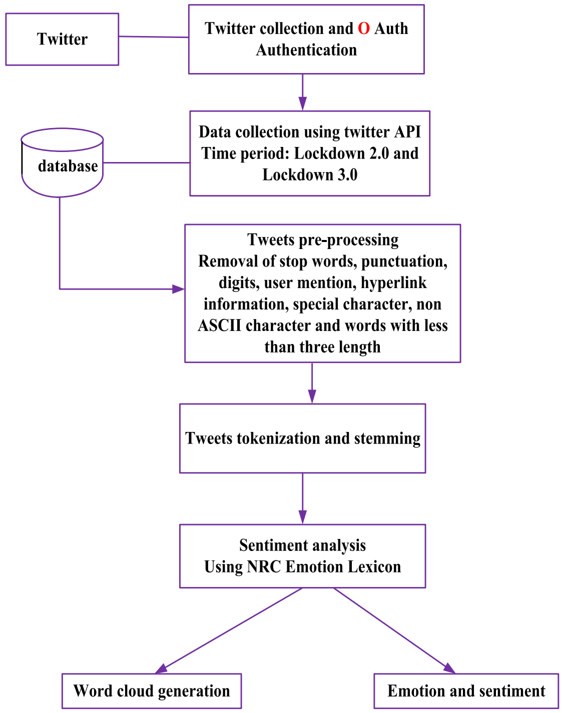

Fig. 1. Flow chart for sentiment analysis.

An overall 47,672 tweets gathered for 3rd lockdown, then examined by 'syuzhet' package in R for presence of emotions, viz fear, joy, sadness.

After pre-processing tweets, National Research Council Canada (NRC) analyzed a lexicon of emotions that can identify the Indians perceptions in eight different sensitive with two feelings through its period. Therefore, every tweet may be falling into different sensitive and feelings. As part of pre-processing the user mentioned hyperlink information is extracted as tweets. After that entire particular characters and non-US characters from Standard Code for Information Interchange, apart from hash tag, are extracted as refined tweet text. In addition, entire behaviors less than three alphabets are not assumed at analysis of tweets, lastly, tokenization and derivation was carried out by Porter Stemmer to perform opinion mining [33].

There are four main steps in the tweets analysis process, which has been followed in the work,

- Data collection

Table 1
Period 1

Location	Total tweets requested
New Delhi	1000
Chennai	1000
Kolkata	1000
Mumbai	1000
Kerala	1000
India	2000

Table 2
Period2

Location	Total number of tweets
New Delhi	1000
Chennai	1000
Mumbai	1000
Kolkata	1000
Kerala	1000
India	1000

- Data preparation
- Building sentiment analysis model
- Visualization of the results

3.1. Data collection

India ranks eighth in the world with more than 300 thousand active cases (before the 2ndwave). India had a peak around in the middle of Sep 2020 nearly 100 thousand cases reported daily, which step by step diminished around 11 thousand cases daily at the end of Jan 2021, then it was raising slowly. At Mar 2021, the cases started rapidly rising. India had 47,000 newly cases that moved towards a 2nd peak. The dataset for this study are the tweets from various states of India. There are two main types of tweets that are extracted from Twitter namely, current and historical tweets. Current tweets are helpful to track keywords or hash tags at real- time and the other can be used to search the past tweets during a predefined time frame. The tweets from Twitter were obtained using Twitter API for two periods they are,

1. March 20, 2020 to March 27, 2020 that is the early days of the National lockdown
2. March 27 2020 to May 3, 2020 a month after the lockdown

The tweets were obtained from Twitter based on latitude and longitude for the following locations for the keywords COVID 19 and Corona in India for both periods as shown in Table 1 and Table 2. A total of 6376 and 12752 tweets were obtained for both periods [34].

A total of 6376 tweets along with re- tweets were obtained in the first period and around 6804 tweets were extracted in the second period, this data set contains the tweet text, author name, re-tweets, location, language, timestamp and other attributes

The initial effort is created to survey investigations in terms of open data source sets related to COVID-19 pandemic. Researcher analyzed using techniques of Artificial Intelligence for data acquisition, segmentation, COVID-19 diagnosis. It did not focus on papers that using publicly obtainable data sets. It could not aspect the Artificial Intelligence (AI) applications of COVID-19 epidemiology and psychology dataset. Rather, a comprehensive overview of COVID-19 open source survey data details using artificial intelligence and statistical methods. Any survey can able to assist the investigations to identify the proper open source data sets. The datasets are compared based on application, type, and size unequal items that give precious information on dataset selection. Furthermore, we highlight future investigation directions based on missed investigation opportunities including missing data sets as a result of which the investigation community may operate on public availability of data [35].

Addition from the current context of the infection necessarily requires a fast publication process. Moreover, non-peer-reviewed study inclusions are supported through its transparent open source techniques that may be separately established. A total of 6376 tweets along with re- tweets were obtained in the first period and around 6804 tweets were extracted in the second period, this data set contains the tweet text, author name, re-tweets, location, language, timestamp and other attributes. Consolidated outlook of taxonomy of open source COVID-19 data sets is demonstrated at Fig. 2.

The data sets are separated into two major types: (i) medical images, (ii) textual data. Data sets depend on medical imaging are put in service primarily for detection and COVID-19 diagnosis. Clinical imageries are chest CT scan/ X-rays. Clinical imaging datasets must assume the approval of patient for preserving patient secrecy. Diagnosis based on clinical imaging reduces the burden of conventional screening based on PCR. Text databases serve 3 major intentions: forecasting the transmission, spread of COVID-19 in terms of reported cases, analysis public emotion / opinion / extracting keywords linked to COVID-19 in popular social media platforms [36].

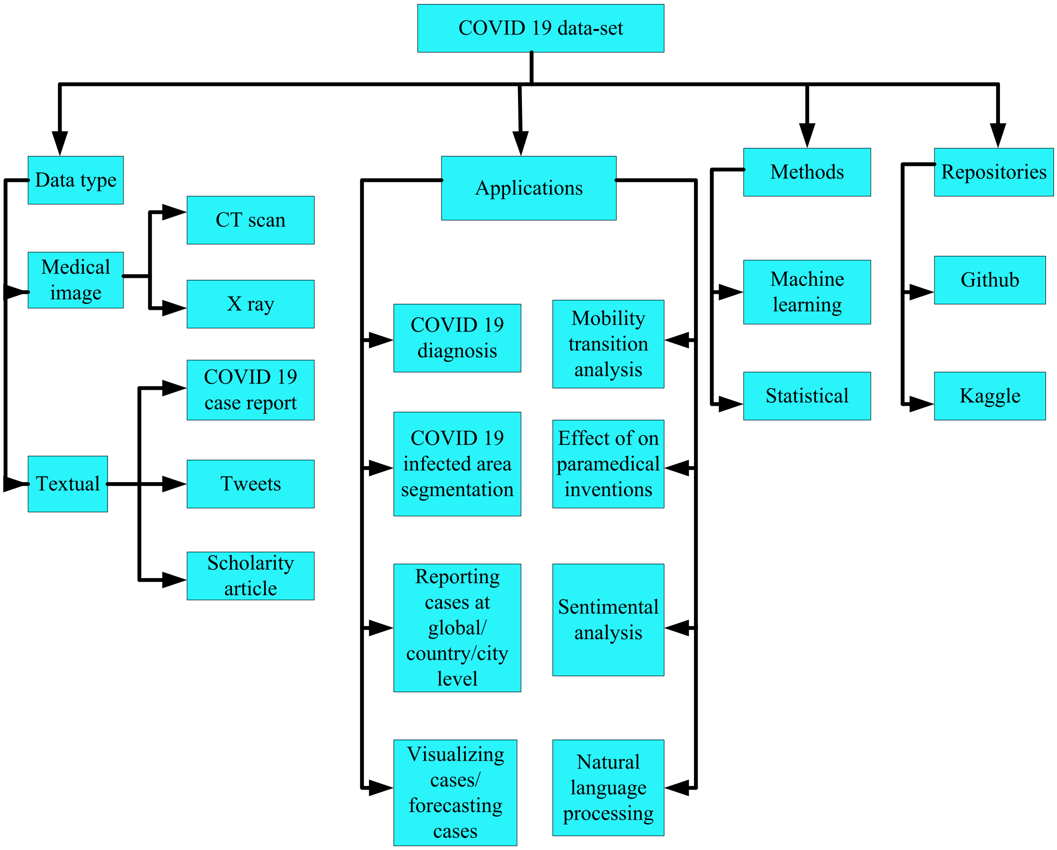

Fig. 2. Taxonomy of COVID-19 open-source data sets.

This graph shows the count of daily cases together with cumulative count of tests conducted per confirmed case or chosen countries around 50,000 cases. The peak lockdown stringency was specified by red line, orange line specifies when it was relaxed, green line specifies when lower stringency. Stringency is measured by Oxford University depending on 17 indicators, like school closing. Figure 3 shows the daily cases and the cumulative number of test cases.

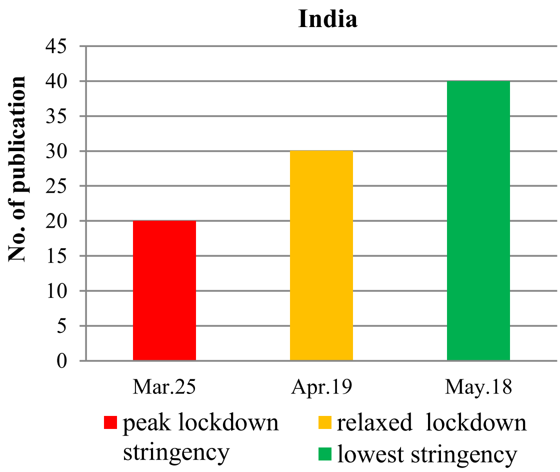

Fig. 3. Daily cases and the cumulative number of test cases.

3.2. Data preparation

This method involves pre-processing and cleaning the tweets for further analysis. Preprocessing the tweet dataset has task series in extracting entire types of unrelated information such as emojis, particular characters, additional blank spaces. It may also make formatting development, deleting copy tweets or tweets, which are less than three characters. The following cleansing activities were performed on the tweet datasets. Figure 4 shows the structure of data preparation.

- Removal of URL links
- Removal of unnecessary spaces
- Removal of punctuations and numbers
- Removal of emojis and special characters

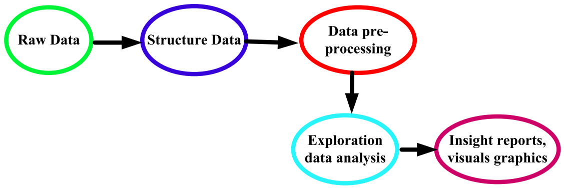

Fig. 4. Structure of data preparation.

- Removal of the words in the other languages

The other pre-processing includes natural languages processing activities such as stemming, vectorization and term document matrix. Vectorization produces a spare matrix representing all words as a number and frequency of each word. Then the term frequency and inverse document frequency matrices are obtained.

Data preparation is a significant part of data science. It involves two concepts, such as data cleansing and function engineering. Both of these are required higher accuracy and performance at machine learning together with deep learning [37].

Data preparation is required due to the presence of raw real word data. The majority of real world data is made up of,

- Inaccurate data
- The presence of noisy data
- Inconsistent data

3.2.1. *Inaccurate data (missing data)*

It has a lot of reasons for missing data, like data not being together continuously, data input error, technical issues, by biometric which require proper data preparation.

3.2.2. *Presence of noisy data (erroneous data and outliers)*

Reason for noisy data existence should be technological issue of gadget collecting data, human error through data entry.

3.2.3. *Inconsistent data*

Due to inconsistencies in data such as duplication of data, the human data entry contains errors in codes or names that violate the data restrictions and necessitates data preparation and analysis [38].

3.2.4. *Machine learning approach*

A Machine Learning Approach is used for text classification, which examines the data is deemed as positive, negative or neutral, also it extracts the features of that model the variation amid the multiple classes and construes, a function is employed for categorizing new cases are hidden. The ML process with text classification is specified as: data pre-processing, feature generation, feature selection, learning approach, model evaluation. This is a general practice to acts data pre-handling before utilizing any sentiment classification approach. Data pre-handling allows making a higher quality text classification as well as lessening the computational complexity. Typical pre-preparing approach combines with parts-of-Speech tagging, stemming with lemmatization, stop-words elimination, tokenization. Features are content traits which is precious for catching few information patterns. The most well-known feature utilized as part of machine learning classification is the nearness or the recurrence of n-grams extricated amid the pre-processing step. In situations where the content length varies incredibly, the use of term frequency (TF) and inverse document frequency (IDF) measurements may be mandatory. In short messages such as tweets, however, words will probably not rehash within one instance, making the double measure of presence as instructive as the counts. Sentiment score computation is the vast process of feature creation. Sentiment computation computes the opinion of a given text from the polarity of words/phrases present in that text. The opinion score of the text can be processed as the normal of the polarities passed on by each of the words in the text. The general thought is to calculate a sentiment score for every tweet, So it would be known how positive or negative.

3.3. *Building a twitter sentiment analysis model*

Almost 80% of world's digital data is shapeless, and high part of it includes social media data. Sentiment analysis tools employ machine learning with natural language processing to automatically organize unstructured text data. Sentiment analysis algorithms can learn as data samples for detecting the tweets polarity at real time. All that needs to be done is to train sentiment analysis models for recognizing sentiment at tweets. The major benefits of Twitter sentiment analysis are,

- Real time analysis
- Scalability
- Consistent criteria

Twitter sentiment analysis model is basically a classification model [39]. The dataset are divided into training and testing sets with class labels assigned

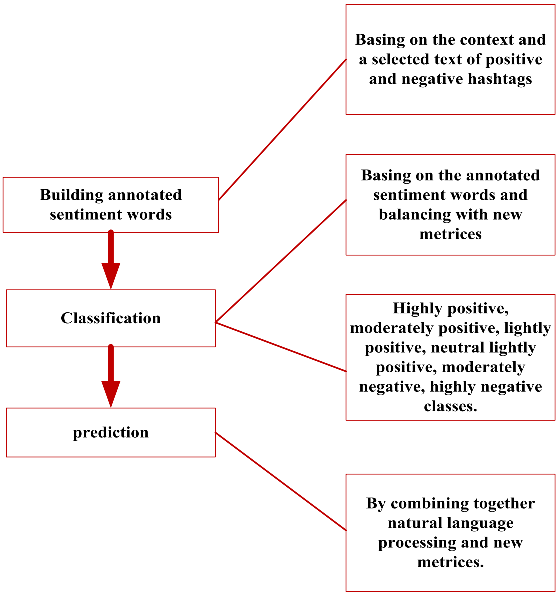

Fig. 5. Sentiment analysis model.

manually for each tweets. Analyzing emotion in twitter data involves numerous steps,

- Collect twitter data
- Arrange your data
- Generate a sentiment analysis model
- Visualize your outcomes

The class labels are one of the three polarities viz, positive, negative, neutral. This kind of model is used to predict the sentiment or polarity of the new unknown tweet. Figure 5 shows the general steps involved in sentiment analysis. Since goal of this investigation is to analyze the sentiments we have used various R packages to analyze the overall sentiment of Indian people during the corona pandemic [40].

Twitter sentiment analysis model is basically a classification model.

3.4. Recurrent Neural Networks (RNN)

The features of the COVID 19 data's are given to the Recurrent Neural Networks (RNN) that contains artificial neurons including one or more than one feedback loops. This RNN is employed for predicting the sentiment analysis of COVID19.To train the recurrent neutral network, the input and target data having training dataset that feds in NNs input layer utilizing back-propagation along stochastic gradient descent for adjusting the node biases including edges weights. The results of NN are likened to the anticipated outcomes. Then, the alteration amid the final and anticipated result is measured, also its result is propagated backward via every node from the output to input layer.The reiteration procedures carry on until matches the final output with the anticipated outcome, whereas the training error lessens until to sufficient state. A simple recurrent neural network has 3 layers: input, hidden, output that are illustrated in Fig. 6; also it shows the architecture of RNN. The input layer consist of N inputs, input is presented in vectors at time t denotes $\{....\{x_{t-1,}x_t, x_{t+1}.............\}\}$ here $x_t = (x_1, x_2, x_4..., x_n)$.

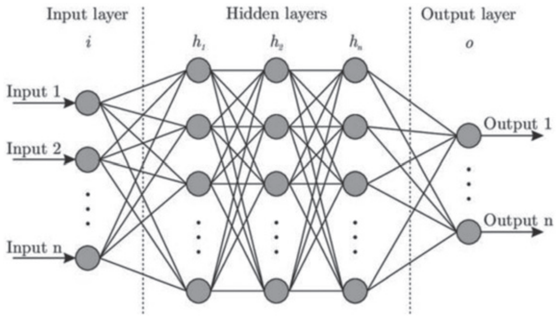

Fig. 6. Architecture of RNN.

The units of input layer are analyzed with hidden layer units. The units are categorized as W_{IH} weight matrix within the hidden layer. The hidden layer has M hidden units implicates $h_t = (h_1, h_2h_3...h_M)$, which is associated each other. The state of hidden layer is considered as,

$$h_t = f_H(O_t) \tag{1}$$

where

$$O_t = W_{IH}x_t + W_{HH}h_{t\text{-}1} + b_h \tag{2}$$

where $f_H(.)$ signifies the activation function of hidden layer, b_h depicts the bias vector of hidden units. The output layer has been linked to hidden layer units via the weighted connections W_{HO}. The output layers of RNN has P elements $y_t = (y_1, y_2, ...y_p)$ which are examined below

$$y_t = f_o(W_{HO}h_t + b_o) \tag{3}$$

here, $f_o(.)$signifies the activation function, b_o implies output layer's bias vector of.

3.4.1. Activation function

Every node in neural networks (NNs) having an activation function connected in it as well as determines through the output of respective node by presenting input or set of inputs. It has many activation functions that are associated with NNs; also *sigmoid* with tanh is utilized typically. To train the classification mode, these activation functions are utilized in the output layer and consolidated with loss functions. The *sigmoid*, tanhactivation functions are expressed below,

$$\tanh(x) = \frac{e^{2x} - 1}{e^{2x} + 1}, \tag{4}$$

$$\sigma(x) = \frac{1}{1 + e^{-x}} \tag{5}$$

This is scaled by scaled *sigmoid* function that are specified using the below equation,

$$\sigma(x) = \frac{\tanh(x/2) + 1}{2} \tag{6}$$

3.4.2. Loss function

Compute the network performance using loss function though it is compared with the output y_t and target output z_t, that are described below,

$$L(y, z) = \sum_{t=1}^{T} L_t(y_t, z_t) \tag{7}$$

Finally, the recurrent neural network is used to classify the sentiment classification as positive, negative, neutral sentiment scores.

3.5. Visualization of the result

The given Fig. 7 displays the intensity of various feelings; they are sad since people are worried about what the day laborers are doing to endure the closure period. When question arose regarding non-availability of alcohol through lockdown there was anxiety over the alcohol addict before the signs of extraction.

In general, it may view, which Indians consider the fight next to COVID 19 in a positive way and most agree with the government for announcing blockade to flatten the curve, which should be seen in tweets, which angered a lot of people because the crash occurred too late.

Lockdown must have been publicized a week earlier. Additionally, few tweets articulated concern that the foreign passengers who flew must have been quarantined by their families before being united. However, blocking response appears to be positive and denotes that India has been able to regulate the corona virus spreading.

Future studies may analyze tweets before and after lockdown and understand if there is a change at sentiment from starting to lockdown end. Additionally,

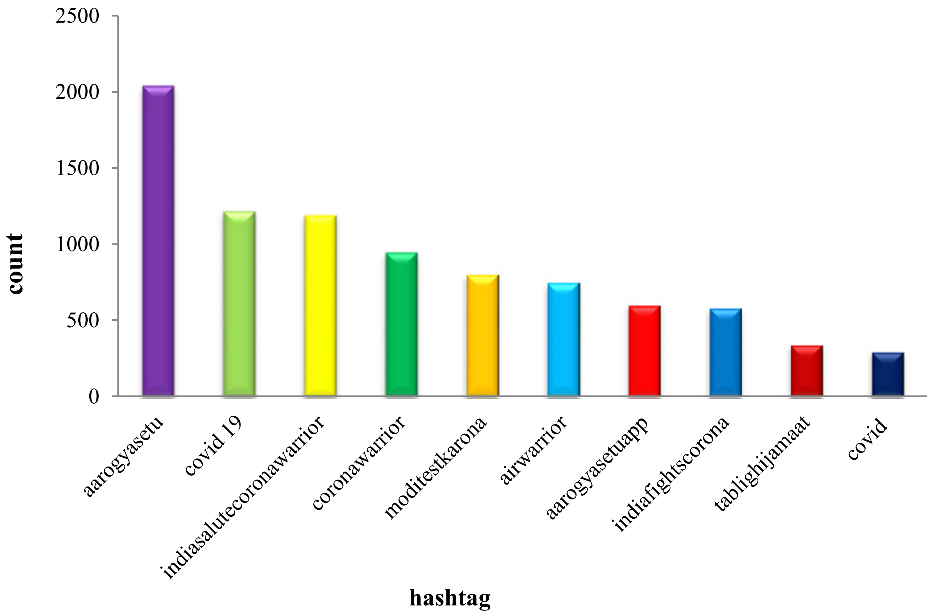

Fig. 7. Graphical representations of sentiments.

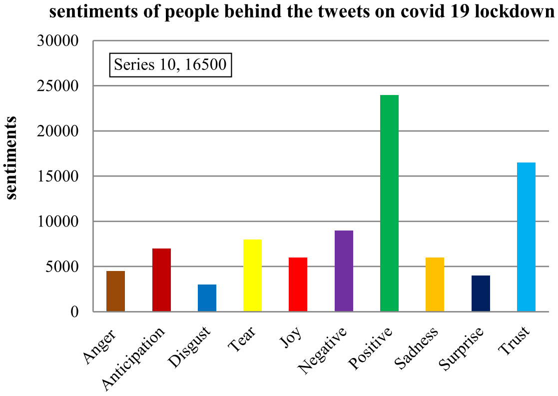

Fig. 8. Top 10 +ve hash tags when lockdown 2.0 in India.

Table 3
Sample sentiment score of the tweets

Tweet	Category	Score
1	“positive”	“0.5”
2	“positive”	“0.5”
3	“positive”	“1.9”
4	“positive”	“0”
5	“positive”	“0.6”
6	positive”	“0”

future studies may view at factors, which involve metal health through blockages and spread of a pandemic. Other area for future investigation should be address false news circulating throughout social media, which affects the mental health of the recipients [41].

4. Results and discussion

Analysis was carried out by R language and world cloud representing main emotions throughout the 3.0 confinement is acquired. AarogyaSetu is top positive hash tag at lockdown 2.0 and India Fights Corona kept the positive hash tag at lockdown 2.0 given in Fig. 8.

This work, sentiment scores of the tweets are automatically assigned to the R function get sentiment () using which the category of the sentiment were also identified [42]. A sample of the tweets score and their category is shown below Table 3.

Twitter sentiment user is classified as 2 sentiments: (i) +ve, (ii) -ve. Twitter users resorted to social media usage platform for expressing its opinion. Attempts have been prepared for understanding the mindset of Indians using R software, throughout current lock-

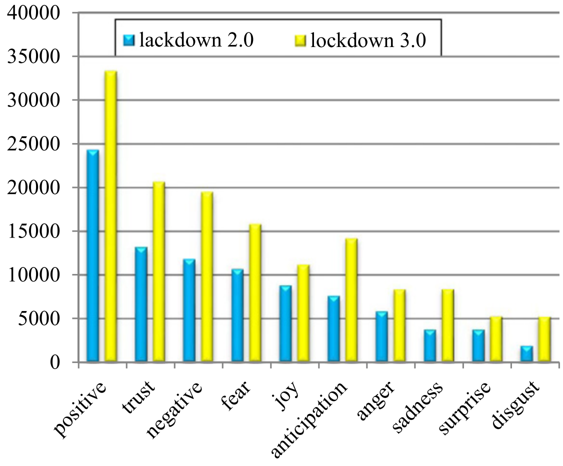

Fig. 9. Twitter user’s emotional analysis– lockdown 2.0 Vs 3.0.

Table 4
Tweet classification for period 1

Negative	Neutral	Positive
1306	2760	2310

Table 5
Tweet classification for period 2

Negative	Neutral	Positive
1874	7302	3576

down 2.0 (April 15, 2020 to May 3, 2020) and lock down 3.0 (May 4, 2020 to May 17, 2020) using the tweets from social media platform Twitter Analysis is carried out using R software. Though this country is positive towards lockdown 2.0, due to sadness, disgust and so on, large part of people show negative sentiment towards lockdown 3.0.We could also derive the various emotions of the tweets for both the lockdown 2.0 and lockdown 3.0as shown below, [43]. Figure 9 shows the twitter user’s emotional analysis–lockdown 2.0 Vs 3.0.

This analysis may assist health professionals for understanding people’s mindsets, authorities to take appropriate action to eliminate the virus, and e-commerce partners for adapting a new attitude by altering supply and demand plans consequently. The three main categories of tweets for both the periods were derived as shown in Table 4 and 5 respectively,

The word cloud for the tweet during the periods is shown in Fig. 10 and Fig. 11 word clouds display the most frequently used word in the text. Here the word COVID has the highest frequency [44].

Fig. 10. Word cloud for period 1.

The sentiment derived from the study of twitter tweets is neutral across the country during 25th March 2020 to 27th March 2020 [45].

4.1. Evolution of COVID 19

The first case of pneumonia is exposed on December 8, 2019 at wet market on Wuhan, capital of

Fig. 11. Word cloud for period 2.

Table 6
Cumulative cases and deaths from COVID 19 pandemic

Date	Events
4 Jan 2020	WHO declared cluster of pneumonia cases at Wuhan, Hubel, China
7 Jan 2020	WHO recognizes COVID-19
13 Jan 2020	1st official COVID-19 case declared in Thailand
17 Jan 2020	Authorities at Nepal, South Korea, Malaysia, France, Singapore, Australia confirm cases
21 Jan 2020	1stCOVID-19 case reports atUSA
22 Jan 2020	WHO get proof from person-to-person migrating of China
23 Jan 2020	China inflict blockade at Wuhan, Xiantao, Chibi
30 Jan 2020	WHO announces COVID-19 international concern public health emergency
31 Jan 2020	United States announces COVID-19 a National Public Health Emergency
2 Feb 2020	First death in Philippines
9 Feb 2020	Count of death at China exceeds the severe acute respiratory syndrome (SARS) of 2002-03
14 Feb 2020	Egypt reports COVID-19 first case on African continent
15 Feb 2020	France reports first COVID-19 death outside Asia
23 Feb 2020	COVID-19 Cases increase in Italy at Largest Outbreak all over the world
26 Feb 2020	Brazil confirms 1st COVID-19 case on South America
27 Feb 2020	1st case of community transmission declared on USA
29 Feb 2020	First death from COVID-19 on USA
8 Mar 2020	Above 100 countries declared the cases Italy enforced quarantine on Lombardy
11 Mar 2020	WHO announces COVID-19 pandemic
13 Mar 2020	Donald Trump announces a national emergency on USA
17 Mar 2020	50 US states contain at least one confirmed case, the initial California state to execute "stay at home" order.
19 Mar 2020	The death count in Italy exceeds China
21 Mar2020	EU suspend public shortage rules for injecting fiscal stimulus in all countries
25 Mar 2020	White House and Democratic Senate leaders and Republican parties on US reach a contract on $ 2 trillion stimulus to help workers, business with health care system reply to pandemic.
26 Mar 2020	United States guides world at COVID-19 cases
2 Apr 2020	Worldwide COVID-19 cases arrive at 1 million
8 Apr 2020	China lift lockdown on Wuhan, 76 days subsequent to include COVID-19
11 Apr 2020	US records 2,000 deaths in a day, greatest number of deaths in a single day recorded via any country
15 Apr 2020	Global COVID-19 cases arrived at 2 million
24 Apr 2020	The death count in US exceeds 50,000
27 Apr 2020	Worldwide COVID-19 cases arrived at 3 million
28 Apr 2020	COVID-19 cases at USA exceed 1 million
21 May 2020	Worldwide COVID-19 cases exceed 5 million
22 May 2020	Brazil exceeds Russia as second country by largest number of cases, subsequent to US.
27 May 2020	The death count in US exceeds 100,000

China's Hubel province. Various groups of pneumonia patients are reported during the last December 2019. The given Table 6 gives the key events timeline of January 2020.

Cumulative cases and deaths of COVID 19 pandemic, death cases began to rise as March 2020 in June, the total cumulative cases is more than 9.2 million, and more than 777,000 deaths over the world [46].

4.2. Observational studies on mental health issues associated with COVID-19

In Table 7, there are 4 studies, entirelyin Chinese centers that observed the frequency of exact variables linked to mental health at people who are affected by COVID 19 outbreak and its outcomes are given below.

On observing the previous outcomes, the study has roughly estimated the frequency of individual mental health indication through nervousness being most common. Both studies linked the anxiety by sleep disturbances. At study of population, poor perception of health are linked by greater rates of anxiety and depression; on contrary, availability of correct information and specific preventive measure utilize, like hand washing, seemed for mitigating such effects. This type of descriptive study should not be recovered from other countries.

4.3. Performance evaluation

The performance of the proposed model is evaluated with the help of accuracy and sensitivity is as follows,

4.3.1. Accuracy

This is the classification proficiency corresponding to the total count of classification tests. Accuracy is given in Equation (8),

$$Accuracy = \frac{TP + TN}{TP + FN + FP + TN} \tag{8}$$

Table 7
Observational investigations on mental health problems associated with COVID 19

Author	Country of origin	Population study	Methodology	Study instruments	Outcomes
Kuo et al., [15]	China	Common population ($n = 1210$)	Survey of online	Depression, Anxiety, Stress Scale (DASS-21); Event Scale-Revised impact	16.5%, 28.8% moderate for depressive,anxiety signs; 8.1% reasonable for rigorous stress
Xiao et al., [47]	China	Clinical staff treats patients with COVID-19 ($n = 180$)	Cross-sectional, self-rate questionnaire	Self-Rating Anxiety Scale; Common Self-Efficiency Scale; Stanford Acute Stress Reaction Questionnaire; Pittsburgh Sleep Quality Index; Social Support Rate Scale	Mean anxiety scores 55.3 ± 14.2; anxiety positively interrelated to stress and negatively with sleep quality, social support, self-efficiency ($p < 0.05$, entire correlations)
Grifoni et al., [28]	China	Common public ($n = 214$); front-line nurse ($n = 234$); non-front line nurse ($n = 292$)	Cross-sectional, survey of self-rate utilizing mobile app	Chinese version of Vicarious Traumatization Scale	Traumatization associated with COVID-19 maximal amid non-front line and front-line nurses ($p < 0.001$); Traumatization between common public maximal to front-line nurses ($p < 0.005$) other than non-front-line nurses
Xiao et al., [47]	China	persons at 14 days isolation ($n = 170$)	Cross-sectional, self-rated questionnaire	SAS; SASR; PSQI; PSCI-16	Mean anxiety score 55.4 ± 14.3; Anxiety is positively interrelated by stress, negatively with sleep quality with social capital; social capital positively interrelated through sleep quality. ($p < 0.05$, entire correlations)

Table 8
Performance comparision of proposed RNN model with the existing method

Methods	Accuracy (%)	Specificity (%)	Sensitivity (%)	Precision (%)	F-Score (%)
Proposed(RNN)	94.5	96.5	97.5	98.5	96.5
FB-DL	90.3	92.3	89.3	93.3	90.32
H-SVM	90.46	93.46	90.46	94.46	93.46
RNN-LSTM	90.3	94.3	94.3	91.3	94.3
MVEDL	9.23	92.2	96.23	94.23	94.23

4.3.2. Sensitivity

It computes quantity of actual positives which is correctly predictable and is formulated as,

$$Sensitivity = \frac{TP}{TP + FN} \tag{9}$$

Table 8 shows the performance comparison of proposed RNN model along with four existing methods. In this, the proposed method is compared with four existing approach such assentiment analysis of COVID-19 using Novel FB-DL, H-SVM, RNN-LSTM, MVEDL. The accuracy of the proposed RNN method is 43.35%, 40.5%, 33.45%, 40.25% is higher than the existing methods, such as FB-DL, H-SVM, RNN-LSTM and MVEDL. The specificity of the proposed RNN method is 33.35%, 42.5%, 31.45%, 30.25% is better than the existing FB-DL, H-SVM, RNN-LSTM and MVEDL methods. The sensitivity is 42.35%, 41.5%, 34.45%, 42.25% is better than the existing FB-DL, H-SVM, RNN-LSTM and MVEDL methods. The precision of the proposed RNN method is 41.35%, 43.5%, 32.45%, 40.25% is better than the existing FB-DL, H-SVM, RNN-LSTM and MVEDL methods. F-score is 43.35%, 40.5%, 33.45%, 40.25% is better than the existing FB-DL, H-SVM, RNN-LSTM and MVEDL methods.

5. Conclusion

This study is successful in its goal of analyzing people sentiments and emotions during the COVID-19 pandemic. The analysis of tweets in the early days of the lockdown shows that the people are neither positive nor negative. They remain marginally neutral. After a month of lockdown, most of them are more positive or neutral. This gives an insight mental feeling of the people in India after the corona attack. When India went into lockdown on 24th March 2020 only 500 positive cases were reported across the country and people were not fearful to the situation, and after a month during the last week of April 2020 these cases had risen to 33,000 with a death toll of 1000 approximately. Even the people remained more positive cases but not fearful. This could be due to the fact that the death rate was low and the recovery rates are high compared to other countries in the world. This kept the people more positive and hopeful. This research can be used for future work to examine the changing emotions and feelings of individuals from these countries and check whether there are significant changes in them over time. Future work includes analyzing people's sentiments on health facilities, government response to the pandemic, offline exams, mental health etc.

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Data availability statement

Data sharing is not applicable to this article as no new data were analyzed or created in this study.

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