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An Emotion Care Model using Multimodal Textual Analysis on COVID-19

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ABSTRACT

At the dawn of the year 2020, the world was hit by a significant pandemic COVID-19, that traumatized the entire planet. The infectious spread grew in leaps and bounds and forced the policymakers and governments to move towards lockdown. The lockdown further compelled people to stay under house arrest, which further resulted in an outbreak of emotions on social media platforms. Perceiving people's emotional state during these times becomes critically and strategically important for the government and the policymakers. In this regard, a novel emotion care scheme has been proposed in this paper to analyze multimodal textual data contained in real-time tweets related to COVID-19. Moreover, this paper studies 8-scale emotions (Anger, Anticipation, Disgust, Fear, Joy, Sadness, Surprise, and Trust) over multiple categories such as nature, lockdown, health, education, market, and politics. This is the first of its kind linguistic analysis on multiple modes pertaining to the pandemic to the best of our understanding. Taking India as a case study, we inferred from this textual analysis that 'joy' has been lesser towards everything (~9-15%) but nature (~17%) due to the apparent fact of lessened pollution. The education system entailed more trust (~29%) due to teachers' fraternity's consistent efforts. The health sector witnessed sadness (~16%) and fear (~18%) as the dominant emotions among the masses as human lives were at stake. Additionally, the state-wise and emotion-wise depiction is also provided. An interactive internet application has also been developed for the same.

1. Introduction

With the sudden eruption of COVID-19 at the offset of the year 2019 and successive unfolding of the disease's infectious nature, the world came to a standstill. This novel Coronavirus has been enticing scientists worldwide to get to its root cause or magnify the potential of introducing a vaccine [1,2]. Several studies [3–5] have also been conducted in this regard. Governments of different countries were left with no choice but to enforce a complete lockdown in their territories. All industries, including businesses, sports, and entertainment, had come to a halt to observe social distancing. Researchers and medical practitioners worldwide are trying their best to find the cure of the disease to attenuate this lethal virus [6–10]. Across the globe, people at all communal levels directly or indirectly face this crisis and find ways to deal with these unusual conditions. However, before making strategies to fight this virus, it is essential to know people's state of mind, emotions, and concerns [11–13]. Intuitively, such a strong pandemic has affected people's day-to-day lives, due to which there is an increase in the usage of social media platforms [14]. We take India as a reference for the study conducted in this paper. Since India has the world's second-largest population and a wider landscape, it was interesting to see various emotional outbreak trends on popular social media platform Twitter [15]. Emotion plays a pivotal role every day in people's lives when they interact or communicate with each other [16,17]. People have expressed their concern regarding several issues. Some were distressed [18–20] with the country's economy's downfall, while others felt happy with our mother nature [21,22].

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Table 1
Summarization of Previous work on COVID-19 analysis.

Ref.	Emotion Label	Dataset	Methodology adopted	Lexicon/ Model used	Advantages	Limitations
[32]	Anger, Anxiety, Indignation, Negative emotion, Positive emotion	Wiebo data pool	Online Ecological Recognition (OER)	LIWC2015 Lexicon	For Policy improvement on mental health	Case study on China from a social media platform
[33]	Anger, Anticipation, Disgust, Fear, Joy, Sadness, Surprise, Trust, positive, Negative	Twitter dataset	Lexicon-based approach	NRC Word- Emotion Lexicon	To understand the changing mindsets of people	Only English tweets were collected for the study
[35]	Level of anxiety	Online questionnaires	ML-DL approach	Hybrid Approach	Understand psychological impact of epidemic on college students	Online questionnaire
[39]	Anxiety, Fear, Sadness, Anger	Questionnaire survey	Lexical oriented approach.	NRC Word-Emotion Association Lexicon	To understand the coping strategies of nursing college students	Online questionnaire
[38]	Willingness to self-isolate	Online questionnaires	Unsupervised learning	Automated Model	To help authorities understand public willingness to self-isolate	Online questionnaire is used and study is restricted to U.S. only

To the best of our understanding, this is the first of its kind analysis on multiple modes about a single category (nature, lockdown, health, education, market, and politics) and the eight emotions revolving around those modes. In this regard, a novel emotion care scheme has been proposed in this paper to analyze multimodal textual data contained in real-time tweets related to COVID-19. This paper studies 8-scale emotions (Anger, Anticipation, Disgust, Fear, Joy, Sadness, Surprise, and Trust) [23–25] over multiple categories such as nature, lockdown, health, education, market, and politics. An interactive web-based application has also been developed for the same. The analysis conducted finds application in many fields. In a democracy, people's opinion matters a lot. People are not just voicing their opinion but are also being heard. The governmental agencies and policy builders need to know what impact their decisions have on people. Another important aspect is that listening to what others feel about a particular situation helps one understand an entirely different perspective towards different aspects or dimensions of that situation. This is significant while policymaking as every section of the society is considered while making inferences about legislative decisions [26–28].

The rest of the paper is organized in the following manner: Section 2 describes the related works. Section 3 describes the methodology adopted and the web application. Section 4 presents the results and conclusion. Section 5 concludes the paper with indications for future scope.

2. Related work

Multimodal emotion analysis is a way to emphasize recognizing emotions towards different modes or aspects of an occurrence [29–31]. During the COVID-19 outbreak, many research work and studies have been conducted to analyze public emotions on various events. These studies helped the government in formulating guidelines and taking strategic decisions to control the infectious spread. Table 1 summarizes the emotion analysis conducted by previous studies on COVID-19.

Understanding people's emotional state in such tough times of pandemic attack helps the government review old policies and formulates new guidelines and takes measures that can motivate the population and restore their physical and mental health. Thus, several studies have been conducted to analyze the public emotions on various events during this pandemic. There are several models proposed for analyzing public emotion during the COVID-19 pandemic.

A simplified approach has been proposed in [32] that analyzes the emotion of 17865 active Weibo users in China, consisting of approximately 25% male users and 75% female users with age groups of 8-56 years. The majority of the users are from Eastern China (approximately 77%) and some from the Central part of China, about 9%, and Western China around 12% had been taken into consideration. They analyzed users' emotions one week before 20 January 2020 and one week after the same date. Their analysis revealed that mean negative emotion in the population had increased significantly in two weeks, including anger, anxiety, and indignation. The results also showed that the words of concern like "Health," "Family," and "Death" increased significantly, indicating that with passing the time, people were getting more concerned about their family and health. Another work [33] analyzed India's emotion during lockdown phase 2 and lockdown phase 3 on the Twitter dataset and analyzed the opinion on e-commerce during this pandemic. Their results showed a change in emotions during different lockdown phases. There was a specific dip in the percentage of emotions like fear, joy, and trust in lockdown three than that of lockdown two. At the same time, there was a certain rise in emotions like anticipation, anger, and disgust. Their analysis also revealed how e-commerce sales trends changed in lockdown two and lockdown 3. This indicated that people's mindset changed from stocking baby products, beauty products, toys and games, sports, and fitness in lockdown 2 to nutrition products, apparel, and household goods in lockdown 3.

Researchers have also analyzed the news headlines of Coronavirus and classified sentiments and emotions associated with the news [34]. The sentiment and emotion analysis was performed on 1,41,208 news headlines from top-rated 25 English news sources between 15 January 2020 to 3 June 2020 containing the keyword "CoronaVirus." The results showed that 52% of the news headlines evoked negative sentiment while only 30% evoked positive sentiments. Others were neutral, that is, 18%. Emotion analyzed in the study showed the highest percentage of fear followed by trust, sadness, anticipation, and anger.

[35] studies the impact of covid-19 on college students in china revealed that approx. 25% of students have experienced anxiety because of this COVID-19 outbreak. The results concluded that the risk factor and academics' delays were the main reasons for increasing anxiety. In contrast, factors like living with parents and having a steady family income were protective factors against experienced anxiety during the COVID-19 outbreak. Like this, Cherish Kay L. Pastor et al. [36] analyzed students' sentiments in the Philippines on online education methodology based on an open-ended questionnaire. Their analysis revealed that most students were not prepared for the online education and were worried about the factors like internet connectivity in the area and other issues.

As the pandemic started, many researchers got the insight of top concerns of tweeters on COVID-19, and Alrazaq et al. [37] do

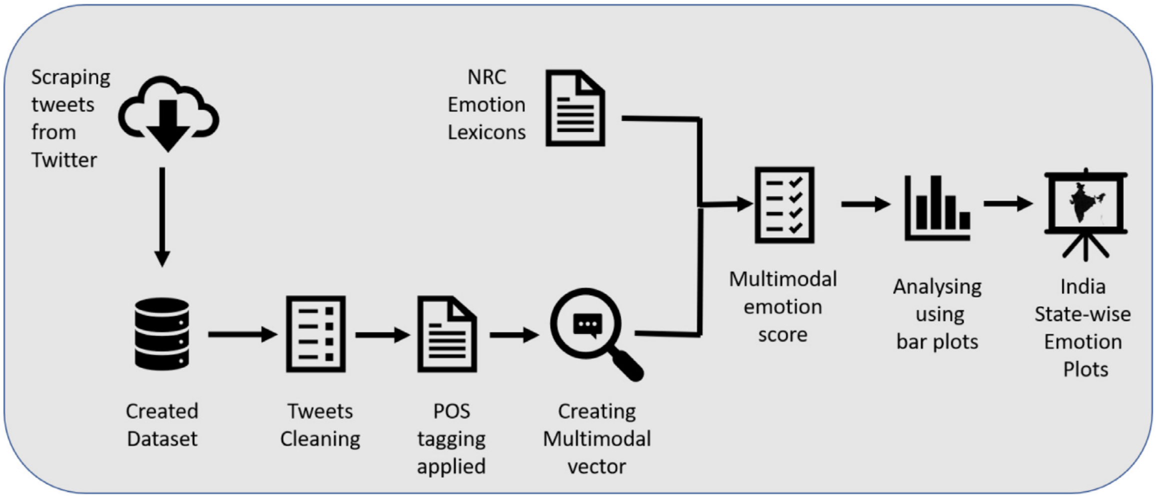

Fig. 1. Emotion-care scheme.

the same in his work. Alrazaq analyzed the 2.8 million tweets, including 167073 unique tweets from 160829 unique users, and identified 12 topics (China, Outbreak of COVID-19, Death causes, Economic losses, Travel bans, and warning.). Their analysis further revealed that people had overall positive sentiments on ten topics and had negative sentiment on two deaths caused by COVID-19 and increased racism.

Joseph Heffner et al. [38] studied the public willingness to self-isolate by analyzing the sentiments on two types of self-isolating guidelines, either threatening or written in the persuasive language. Their results showed that although people evoked negative sentiment for threatening guidelines, they showed a willingness to self-isolate themselves.

3. Materials and Methods

The dataset of tweets has been created with the help of Twitter streaming API[1]. The proposed emotion care scheme operates on real-time tweets. It then recognizes various modes on which the tweet talks about, with the help of a multimodal vector list related to COVID-19 happenings. Further, it analyses the emotion indicated for each model. This process is executed for every tweet of the curated dataset. Finally, all tweets about six different modes have been grouped to achieve a mode-wise analysis. This workflow is depicted in Fig. 1 and discussed in two sub-sections, 3.1 and 3.2.

3.1. Dataset Collection and Pre-processing

The Twitter tweets are scraped from the 'scrape-twitter' API using JavaScript. A dataset[2] is created with the following attributes: tweet posted time, location, and India tweets. The various locations of tweets include all states and union territories of India. The tweet posted time is considered for the period '25-03-2020' to '09-06-2020' during various lockdown phases in India during the COVID-19 pandemic. Within this research paper's scope, only 'English' tweets are considered with the following hashtags #CoronaVirus, #LockdownDiaries, #Lockdown, and #COVID-19. The words present in the multimodal vector list were compared with the adjectives and adverbs generated by POS tagging of tweets using Stanford POS Tagger[3]. The resultant list is then compared against the NRC

Fig. 2. Word Cloud of tweeted words.

emotion lexicon[4] to determine its emotion score using frequency of terms appearing in tweets and score provided by NRC emotion lexicons.

In this research paper, the NRC emotion lexicon is used [40]. NRC emotion lexicons are considered for scoring parameters of tweets. The NRC emotion lexicon consists of each word's emotion score present in respect of emotion: anger, anticipation, trust, sadness, joy, disgust, fear, and surprise. Fig. 2 illustrates the most frequently used terms on Twitter during the pandemic. A large dataset of ~8,84,111 tweets has been segregated to achieve multimodal tweets in each emotion category.

Tweets' cleaning is performed in this section, where basic NLP operations for tweet cleaning are applied [41]. The tweets are first converted into lower case strings. Then, the user mentions, retweets, special characters (except a-z, A-Z), links, and punctuations are removed swiftly and effectively. The stop words are removed by using stop words imported from the NLTK library. Cleaned tweets are processed for tokenization, where each sentence is disintegrated into words to be considered emotional words. The list of words is simplified into unique words as it contains multiple duplicate words. NRC emotion lexicons are a .csv file converted into a data frame after removing 'Nan' values by replacing them with

1 https://developer.twitter.com/en/products/twitter-api
2 https://github.com/Piyush2912/Twitter_dataset
3 https://nlp.stanford.edu/software/tagger.shtml
4 http://saifmohammad.com/WebPages/NRC-Emotion-Lexicon.htm

Table 2
Multimodal Vector.

Multimodal Category	Multimodal Terms
Nature	‘environment’, ‘pollution’, ‘polluted’, ‘pollute’, ‘sky’, ‘stars’, ‘nature’, ‘earth’, ‘locusts’, ‘cyclone’, ‘garden’, ‘geography’, ‘greenhouse’, ‘habitat’, ‘sun’, ‘moon’, ‘peacock’, ‘bird’, ‘butterfly’, ‘weather’, ‘climate’, ‘marine’, ‘snow’, ‘species’, ‘natural’, ‘island’, ‘sunlight’, ‘sunny’, ‘sunrise’, ‘sunset’
Lockdown	‘home’,‘stay’,‘safe’,‘lockdown’, ‘extended’, ‘confinement’, ‘quarantine’, ‘curfew’, ‘holiday’, ‘imposing’, ‘incurable’, ‘industry’, ‘isolate’, ‘starvation’, ‘social’, ‘distancing’, ‘restriction’, ‘captive’, ‘homecare’
Education	academic’,‘online’,‘education’,‘study’,‘student’,‘teach’,‘coach’,‘train’,‘school’,‘college’,‘exam’,‘grade’,‘graduation’,‘university’,‘placement’, ‘teacher’,‘madam’,‘scholar’,‘homework’,‘master’,‘institute’,‘mentor’, ‘subject’, ‘stationary’, ‘tuition’, ‘screen’, ‘professor’, ‘lecture’, ‘class’, ‘lab’, ‘book’
Politics	‘civil’,‘politics’,‘government’,‘govt’,‘rajya’,‘sabha’,‘party’,‘elect’,‘lok’,‘cm’,‘pm’,‘policy’,‘strategy’,‘governor’,‘minister’,‘summit’, ‘opposition’,‘scheme’,‘majority’,‘serve’,‘manifesto’,‘society’,‘mayor’,‘power’, ‘affairs’, ‘diplomacy’, ‘alliance’, ‘coalition’, ‘politician’, ‘legislation’, ‘guidelines’
Health	‘patient’,‘virus’,‘healthy’,‘test’,‘hospital’,‘medical’,‘vaccine’,‘disease’,‘doctor’,‘nurse’,‘infection’, ‘transmission’,‘mask’,‘handwash’, ‘immune’,‘fitness’,‘sanitize’,‘disinfect’,‘medicine’,‘homeopathic’,‘hygiene’,‘ill’,‘cough’,‘breath’,‘lungs’,‘ventilator’,‘oxygen’,‘recovery’, ‘spread’,‘outbreak’,‘pandemic’,‘epidemic’, ‘suffocation’, ‘metabolism’
Market	‘essentials’,‘gdp’,‘economy’,‘recession’,‘business’,‘tax’,‘customer’,‘grocery’,‘revenue’,‘stock’,‘gst’,‘sale’,‘salary’,‘mall’,‘share’, ‘shareholder’,‘shop’,‘manufacture’,‘marketplace’,‘mart’,‘material’,‘income’,‘stake’,‘statistics’,‘store’,‘subscription’,‘merchandise’, ‘supply’,‘demand’,‘trade’,‘advertisement’,‘wholesale’, ‘retail’, ‘exchange‘

zero. Then, the dataset tweets are used for analyzing multimodal categories, as discussed in the next section.

3.2. Methodology

The proposed scheme evaluates the emotion score spanning over multiple modes. Further, the modes have been hand-picked by realizing the severity of the situation on its associated dimensions. A multimodal vector (shown in Table 2) has been created after examining the most frequently found words in the tweet dataset using the term frequency-inverse document frequency (TF-IDF). The multiple modes considered for emotion analysis are- Nature, Lockdown, Education, Politics, Health, and Market.

T = {t1, t2, tn}, is the set of tweets obtained from Twitter streaming API for each tweet. Each tweet may carry emotion about different modes, and different modes can be described by various terms or phrases in the tweet text. For accomplishing this, we have considered Mk = {m1k, m2k, ..., myk}, is the set of multimodal terms and Mc = {Mc1, Mc2, ..., Mck}, is the set of multimodal categories. Consider the case; a user might refer to the terms’ vaccine’, ‘medicine,’ ‘doctor’ or ‘treatment,’ by which the user refers to the health mode of the Indian citizens. So, ‘health’ can be considered the multimodal category, and words’ vaccine’, ‘medicine,’ ‘doctor,’ and ‘treatment’ are analogous multimodal terms for health. The problem is to identify multimodal emotion intensity. This can be produced by collecting multimodal scores of each tweet. A score of a multimodal category Mc in a tweet is defined as:

E = [Anger, Anticipation, Disgust, Fear, Joy, Sadness, Surprise, Trust]

$$\sum_{i=1}^{6} Mk(i) \cap T = Cw, \tag{1}$$

where *Cw* is Category wise words,

$$POS(CW) = AnA, \tag{2}$$

where *POS* symbolizes POS tagging of Tweets,

$$\sum_{x=1}^{8} AnA \cap NRC(E(x)) = Emotion\_Score, \tag{3}$$

where AnA is a set of Adjectives and Adverbs, x is an element of E

With this multimodal vector, the list of adjectives and adverb words present in processed tweets after POS tagging is matched, and a resultant list is created for common words. The common word list is compared with the NRC emotion lexicon word list to determine each word’s emotion score. Based on multimodal categories, a dictionary of words is created from the resultant list with keywords and value as their frequency of occurrence in tweets for each category. Each category’s scores for the following emotions: anger, anticipation, disgust, fear, joy, sadness, surprise, and trust are calculated using Algorithm 1. Based on their emotion score, the results are analyzed by using bubble plots.

Algorithm 1

```
T = List(t)
Ct = List()
w = Set()
At = List(multimodal_terms)
csv = DataFrame()
def clean(T):
for each t∈T do:
t.remove_hyperlinks()
t.remove_punctuation()
Ct.append(t)
end for
return Ct
def category_wise(Ct, w, At):
for each t∈Ct do:
w = Set(t.split())
if w intersection At != NULL do:
csv.append(t)
end if
end for
return csv
def pos_tagging(csv):
for each t∈csv do:
pos_tagged = List(pos_tag(t))
if word_class == adj or word_class == adv
pos_words.append(word)
end if
end for
return pos_words
def lexicon(pos_words):
for word in lexicon_words do:
if word intersection pos_words != 0
do: emotion_words.append(word)
end if
end for
return emotion_words
def count_frequency(emotion_words):
for each emotion_words∈tw do:
word_count += 1
word_dict.add(emotion_word,word_count)
end for
return word_dict
def scoring_system(word_dict):
for row in lexicon_words.itertuples():
if key,value in word_dict.items():
if (row.key ==1):
value += 1
end for
end for
end
```

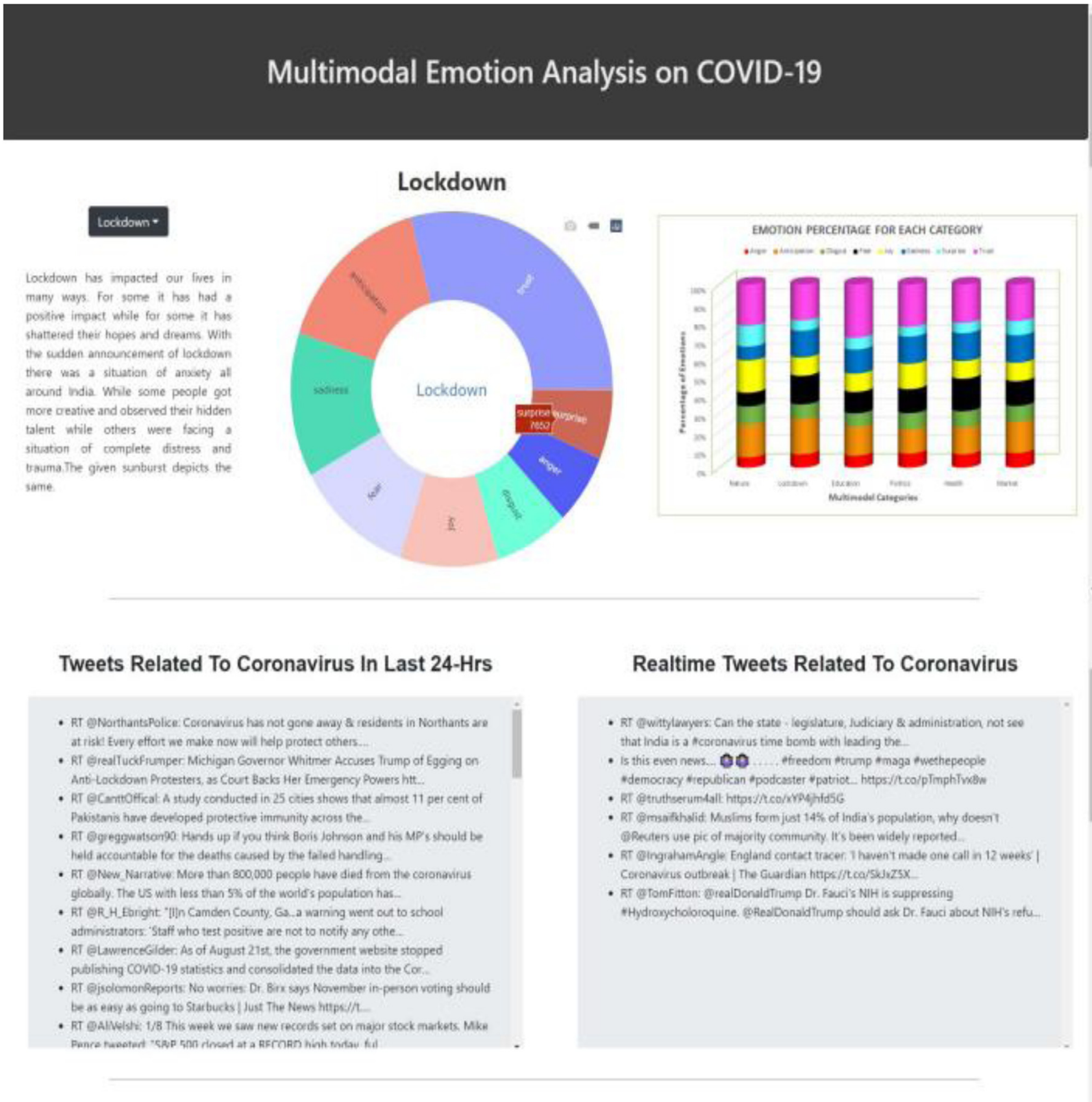

Fig. 3. Web Application https://emotionofindia.herokuapp.com.

This algorithm is used for calculating the score of each multimodal category. In this algorithm, 'T' is the list of 't' tweets, 'Ct' is a list obtained after cleaning of t tweets, 'w' is a set of tokenized words from 't' tweets, 'At' is a set of multimodal terms and 'csv' is the two-dimensional data frame which after processing forms different category wise tweets. The clean function is used for cleaning of tweets. The category wise function is used for separating tweets based on multimodal terms. The POS tagging function is used for each category to determine adjectives and adverbs in 't' tweets. The lexicon function is used for generating a list of common words from POS tagged words and lexicon words. The count frequency function is used for generating a dictionary where the key is word and value is the frequency of the word in the 'tw' list of tweets. The scoring system function is used for calculating the emotion score for each multimodal category.

Figs. 3 and 5

The method used to form the following emotion score chart, as shown in Fig. 4, is all part of a single function that was applied to the dataset. The values for the graph were implemented with the scoring system. POS tagging of all the tweets is conducted wherein the adjectives and adverbs in each tweet were identified. After that cleaning of tweets is performed, a list of separated words is obtained and detected in the NRC emotion lexicon. NRC emotion lexicon consisted of words with their respective emotion scores. A list of common words were obtained, which were present in both: NRC emotion lexicon and tweets. With these common words' help, a dictionary was created, which consisted of the words with their respective frequency appearing in overall tweets.

A scoring system was created for each of the eight emotions studied in this analysis - anger, anticipation, disgust, fear, joy, sadness, surprise, and trust. The scoring system calculated the emotion score using the dictionary created and finding the words in NRC emotion lexicons for their respective emotions' values. Based on the values of emotions, 'state-wise-emotion-count-dictionary' was created. It consisted of the names of states along with their emotion score. It was then written in a CSV file. This CSV file included all states and union territories with their respective emotion score.

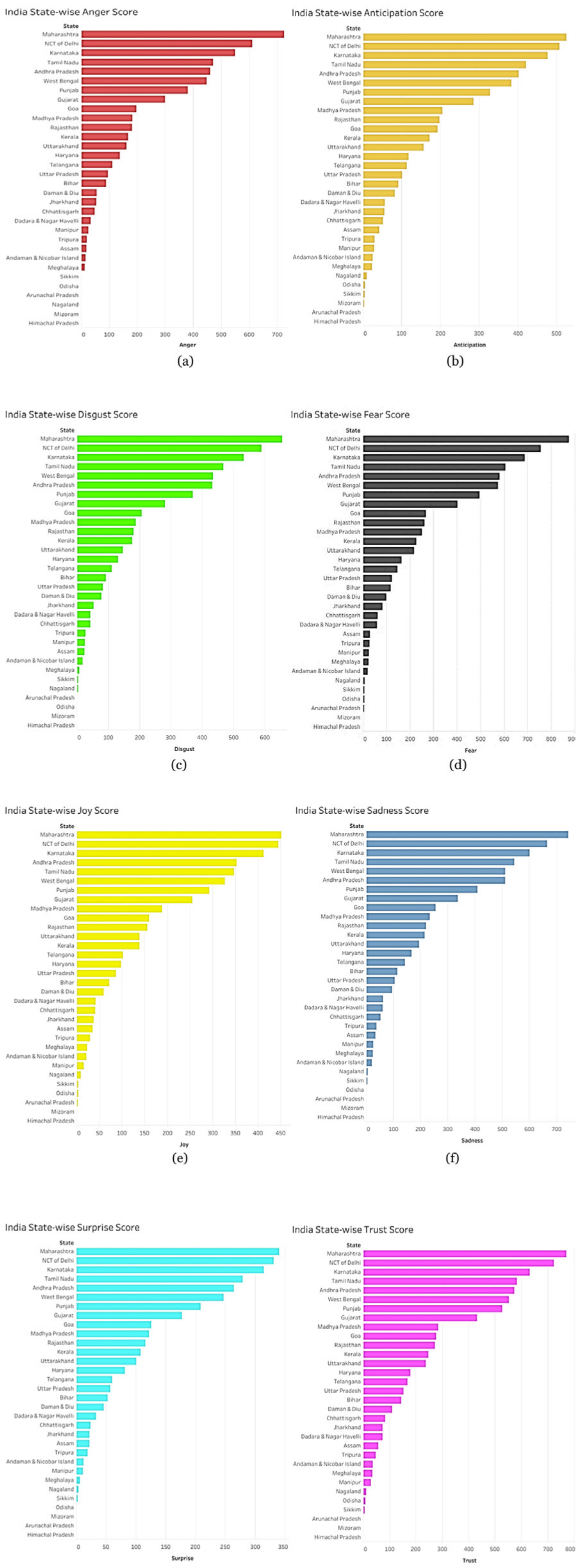

Fig. 4. Indian State-wise Emotion Score: (a) Anger; (b) Anticipation; (c) Disgust; (d) Fear; (e) Joy; (f) Sadness; (g) Surprise; (h) Trust.

3.3. Web Application

Even though there is less number of studies in understanding the emotional unrest among the Indian public, in particular further, the existing studies deal with the overall emotional and behavioral analysis of the public during the COVID-19 attack, rather than lockdown-wise analysis. As an outcome of our study, we also present a web portal to display the emotional unrest in India during COVID-19, based on streaming data of Twitter. This web portal provides visualizations of state-wise and lockdown-wise analysis of emotions during COVID-19. The users are facilitated with two different drop-down menus types, which are based on states and emotions. Based on the user's choice, the analysis on the web platform is updated. The web portal also displays a section wherein the real-time tweets based on #COVID19 are constantly refurbished, as shown in Fig. 2.

3.4. India State-wise Emotion Analysis

Fig. 4 depicts the emotion of the population from different states of India. Maharashtra can be seen at the top of every emotion score, followed by the NCT of Delhi and Karnataka. These states were worst hit by the pandemic, which led to a sudden and massive rise in coronavirus cases. These could be higher fear, anger, disgust, and sadness score in these states. While at the same time, they have also seen immense growth in the number of recovered patients, raising trust and joy among the people. This same trend is followed in other states like Tamil Nadu, West Bengal, Andhra Pradesh too.

4. Results

The proposed multimodal emotion care scheme enables us to understand different dimensions of the same problem that people are talking about. Fig. 6 is a clear depiction of emotions towards different modes. The emotion 'joy' represented by yellow color has been lesser towards everything (~9-15%) but nature (~17%) due to the obvious fact of lessened pollution. But Fig. 6 presents emotion-wise scanning of these modes. The education system entailed more trust (~29%) as compared to any other category. Teachers' fraternity stood to affirm not to let the students suffer due to this pandemic. The health sector witnessed sadness (~16%) and fear (~18%) as the dominant emotions among the masses as human lives were at stake. Convincingly, the public was not relatively angry towards the whole situation.

Coronavirus pandemic has been one of the most unexpected events for the whole world. It has caused distress and panic almost everywhere. Even the most powerful nations have not been able to control its spread successfully and have surrendered to this problem. While some countries like Sweden, South Korea, and Tajikistan have resolved to herd immunity as a solution, others like China, the USA, India, and Italy have considered lockdown as the best possible solution.

Millions across the world were confined to their homes, offices and businesses were shut, and economies were on the verge of collapse. During these stressful times, it is very important to check for the mental health of the citizens. Conducting checks on how people feel towards different situations and events happening around them is important because there can be no productivity unless the mind is healthy.

This section depicts the analysis. There has been a wide variety of emotions that people have expressed towards the lockdown. Some of them taken into account for this paper are -: anger, fear, joy, disgust, anticipation, surprise, sadness, and trust.

Despite the state and central governments' massive efforts, Maharashtra, Uttar Pradesh, Delhi, Tamil Nadu, Karnataka, Rajasthan, Madhya Pradesh, and Haryana have been worst affected by Coronavirus. The analysis has depicted this. The people have mostly been very patient during the lockdown period and have contributed their bit to stop the spread chain of COVID-19. They have shown trust in the governmental policies and decisions as well as in their fellow citizens. Even after all this, due to the rapid spread of the

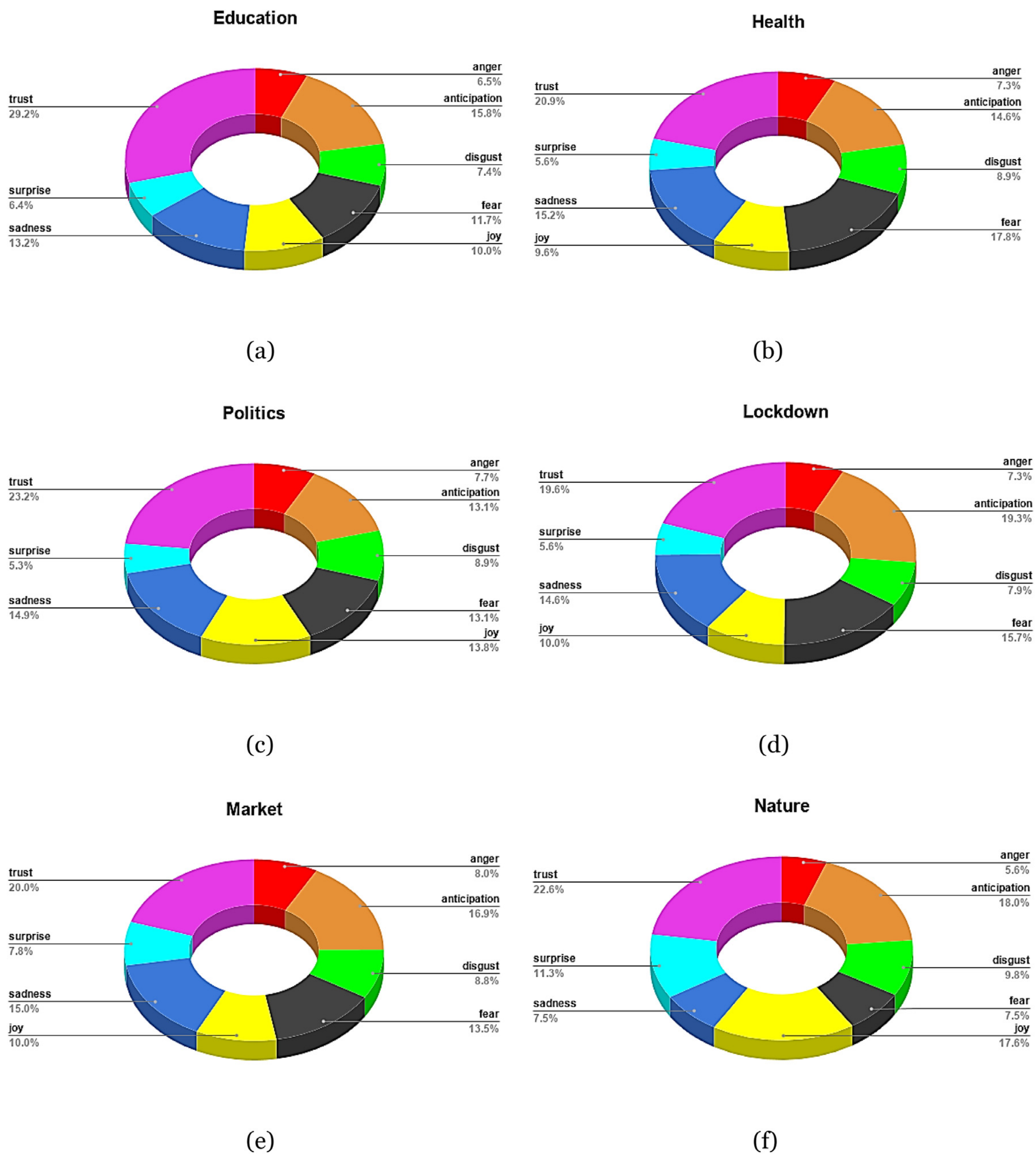

Fig. 5. Multimodal Emotion Analysis: (a) Education; (b) Health; (c) Politics; (d) Lockdown; (e) Market; (f) Nature.

virus, people have been quite fearful about catching an infection. The rising death toll can be another cause of distress and sadness.

Most people have been fearful and unsure about the outcomes of lockdown. Unemployment, working from home, a falling economy, and losing close ones have taken a toll on people's emotional health. Despite all the shortcomings, people have been trying to look at the bright side of things. They have widely trusted the capabilities of teachers and schools to cope up with the changing education system. Reduction in pollution levels has been another cause of contentment amongst people. There has been a lot of anticipation regarding the outcomes of lockdown and its impact on the economy. People have been looking forward to the governmental policies towards the unlocking procedure.

Fig. 6 depicts mode-wise emotion distribution during the lockdown period. COVID-19 has clearly, not just taken away jobs and the economy but has also affected people's mental health adversely. Living away from family trapped in foreign lands, losing loved ones, and not attending their funerals, wearing masks every time you step is not easy to adapt. The new normal is not normal for people. On the other hand, many citizens have been able to cope up with the changing scenario. They are patiently waiting for things to get back to normal and focus on their personal growth.

5. Reflections

As COVID-19 continues to extend its roots all over the world, we continue to gain an understanding of its lasting consequences on society. Besides having intimidating effects on the world economy and people's physical health, the pandemic also posed unusual human behavior challenges.

This paper considered the significance of public emotions and their influence on individuals' mental states during this catastrophe. Tweets posted across India from various states in different lockdown phases were analyzed to understand the people's psy-

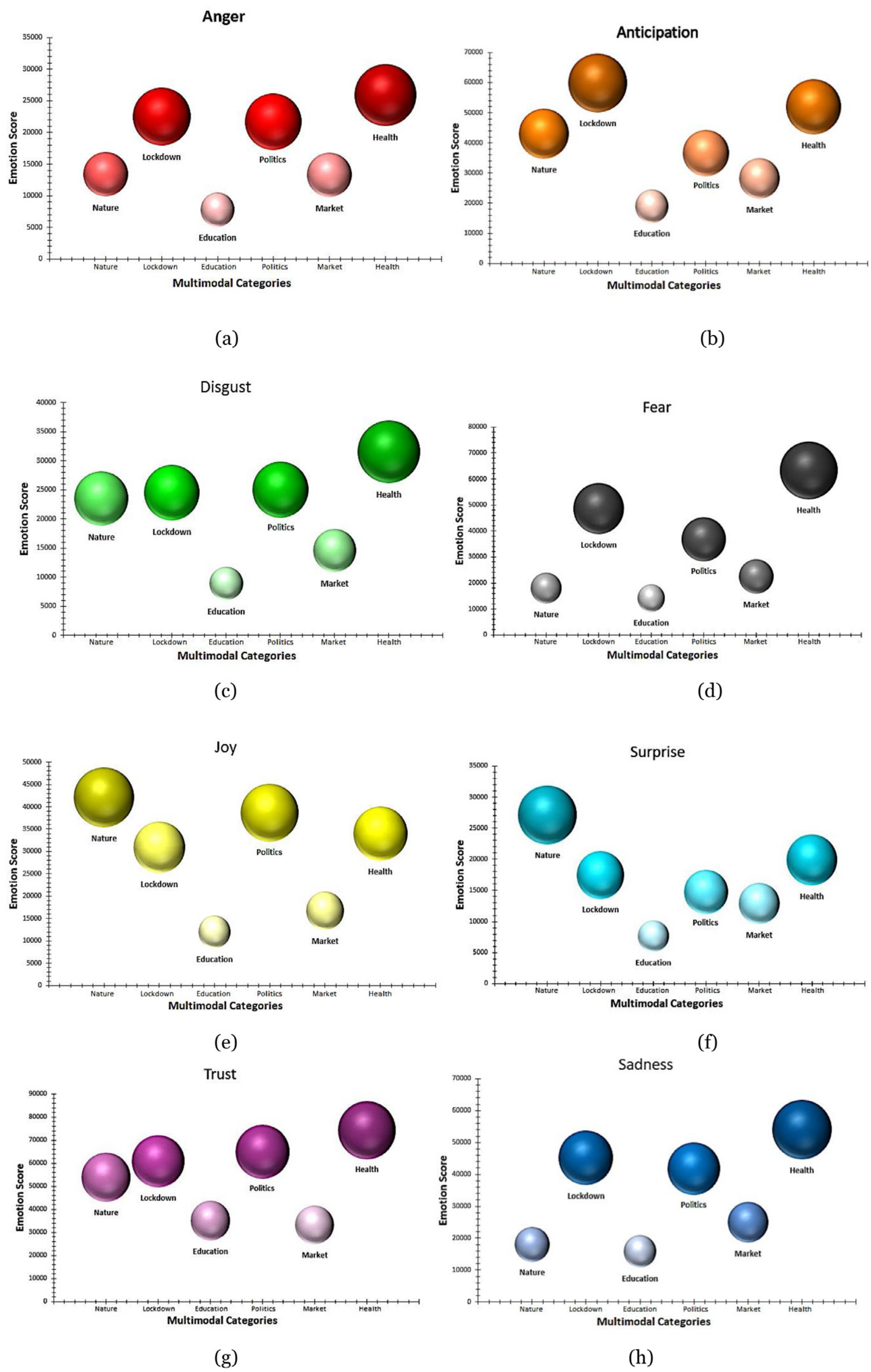

Fig. 6. Emotion intensity bubble plots pertaining to six modes: (a) Anger; (b) Anticipation; (c) Disgust; (d) Fear; (e) Joy; (f) Surprise; (g) Trust; (h) Sadness.

chological health. Emotion analysis across different states has been plotted, denoting the intensity of emotion in the country's top affected states. The fluctuations of different emotions during each lockdown phase have also been visualized. With this analysis's help, policymakers can have a psychosomatic assessment of public health and can act accordingly to overcome this pandemic situation together. The usage of deep learning approaches might also fine-tune the current scheme [42,43]. The idea of sustainability lies somewhere in resolving the current issues and looking out for long-term solutions to combat similar problems in the future.

All in all, lockdown would not have been imposed if we would have been prepared for such pandemic situations physically, mentally, economically, and emotionally. Adopting the right sustainability measures at the right time strengthens the system altogether. These proactive measures also look for long term help centers for people all across the globe. We must identify the problems to the core and then work on each one of them. A country leads by its citizens, and it is equally important to maintain people's emotional and mental health.

6. Conclusion

This paper presents an emotion care scheme and a web-based platform to recognize people's emotional state throughout the ongoing COVID-19 crisis, taking India as a case study. With the help of this research, health organizations and higher authorities will be able to have better insight into people's emotional health and interpret the way people react to various day-to-day decisions. The proposed scheme currently works on Twitter data. However, the scheme is scalable if data from different social media platforms are incorporated. The model is fully functional, but its horizon can be widened by including different languages. Also, the number of emotions considered can be increased to have an even more fine-grained analysis.

Credit author statement

Vedika Gupta: Conceptualization, Methodology, Software **Nikita Jain and Piyush Katariya**: Data curation, Writing- Original draft preparation. **Adarsh Kumar, Senthilkumar Mohan and Ali Ahmadian**: Supervision and Validation of Data- Reviewing Original draft **Massimiliano Ferrara:** Reviewing and Editing

Declaration of Competing Interest

The authors declare that they have no conflict of interest.

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