Foundation University Journal of Engineering & Applied Sciences
Vol. 1, Issue. 1. June 2020

Research article

Decision Support System for Measuring the User Sentiment towards Different COVID-19 Vaccines

Afeefa Asghar[1], Ali Zaman[2*], Saif Ur Rehman[3*]

[1]University Institute of Information Technology, PMAS Arid Agriculture University, Rawalpindi, Pakistan
[*]Corresponding Author: Saif Ur Rehman, Email: saif@uaar.edu.pk

Abstract:

It's been a long time since the (COVID-19) engulfed the entire planet, upsetting normal schedules, destroying economies, and killing millions of people all over the world. The pandemic brought the entire world together in an endeavor to discover a cure and promote inoculation. The first round of vaccines began near the end of 2020, contrary to popular belief, and various nations began the inoculation drive very quickly while others kept it together fully expecting an effective preliminary. Web-based media is blocked with a wide scope of both positive and negative stories in the developing Covid conditions. Numerous individuals were anticipating the vaccination, while others were mindful about the side effects and the fear-inspired notions bringing about mixed emotions. This article performs sentiment analysis, which will be utilized in a choice emotionally supportive network in discovering the viability of COVID-19 vaccines among various nations. We have trained deep long short-term memory (LSTM) models to achieve state-of-the-art accuracy in estimating sentiment polarity and emotional state from extracted tweets. The proposed technique decides public sentiments towards COVID-19 vaccines assisting the healthcare authorities with breaking down their reaction. The results show the mentality of individuals towards various vaccine brands as for their various responses to the Covid-19 vaccines.

Keywords: Decision Support System; Sentiment Analysis;

1. Introduction

The COVID-19 has spread fast across Europe and eventually around the world after the first patient was detected in Wuhan, China, in December 2019 [1]. Coronavirus is a virus that can cause severe respiratory disease [2]. More than 2.17 million people have died as a result of this. Since March 2020, an outbreak of this virus has also been growing. Beginning on March 22, 2021, the number of confirmed cases peaked at 4.3 million and 29.8 million, respectively. COVID-19 has claimed the lives of more than 3.99 million people all across the world. As indicated in Figure 1, the worst affected nations in terms of cases and mortality are the United States, India, and Brazil [3].

DOI: *10.32604/x.2021*

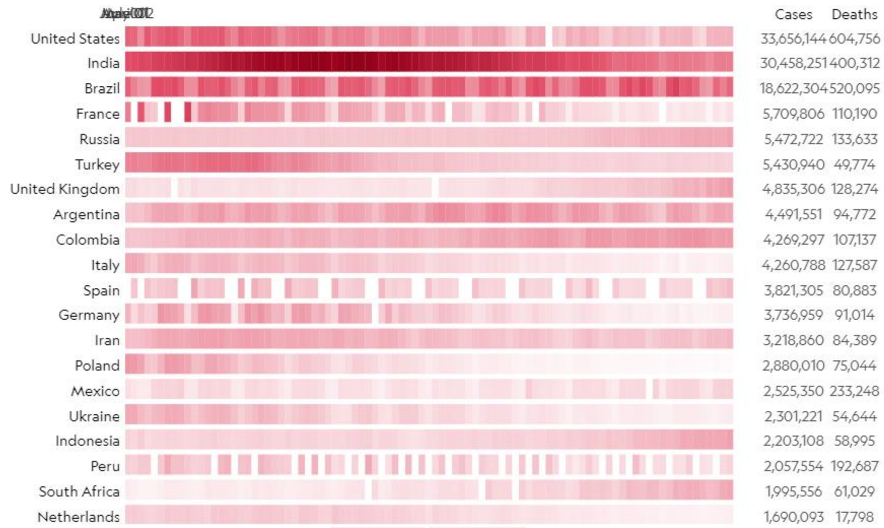

Figure 1: COVID-19 cases and deaths reported country-wise

On December 14, 2020, UK experts informed the World Health Organization (WHO) about the Covid variations, and preliminary studies revealed that this variation might spread fast from person to person. According to scientists, the COVID-19 variant, which was originally first detected in the UK, is up to 100 percent more hazardous than earlier strains [4]. Coronavirus crises have damaged individual psychological well-being because of tragedy in business, education, and employment, generating insecurity, passionate detachment, uncertainty, and sadness [5]. This pandemic circumstance switched the typical daily practice of individuals up the world, for example, academic exercises moved from physical to online mode, change in the way individuals cooperate every day, conduct business, or do shopping [6]. Even though it upset all the exercises, individuals from various societies didn't respond constantly to the pandemic similarly. This cultural gap has been highlighted about the Covid outbreak in some studies [7]. Using Twitter data from multiple nations across three continents, researchers looked into the feelings of people from various cultures about their governments' decisions to manage the Covid outbreak [8, 9]. Asia is represented by Pakistan and India, North America is represented by the Canada and United States, while Europe is represented by Sweden and Norway. The exploratory findings revealed a strong emotional connection between India and Pakistan [10, 11].

Currently, the COVID19 vaccine is being used in several countries throughout the world to treat this deadly virus. As seen in Figure 2, Western countries are leading the way in COVID19 vaccination, while African countries lag. Margaret Keenan, a UK grandmother, will be the first person on the planet to get the COVID-19 vaccination on December 8, 2020. Sandra Lindsay, a persona care worker who was shot in Toronto, was the first American to receive the vaccine at the Long Island Jewish Medical Center, followed by Anita Quidangen, also a personal care worker who was shot in Toronto, GunnBritt Johnsson from Sweden, and finally the 91-year-old. Manish Kumar, a clinic cleaner, is the first Indian to be vaccinated on January 16,

2021. Pakistan will begin immunization on February 2, 2021, with Rana Imran Sikander of the PIMS emergency clinic in Islamabad serving as the first person to get the vaccine.

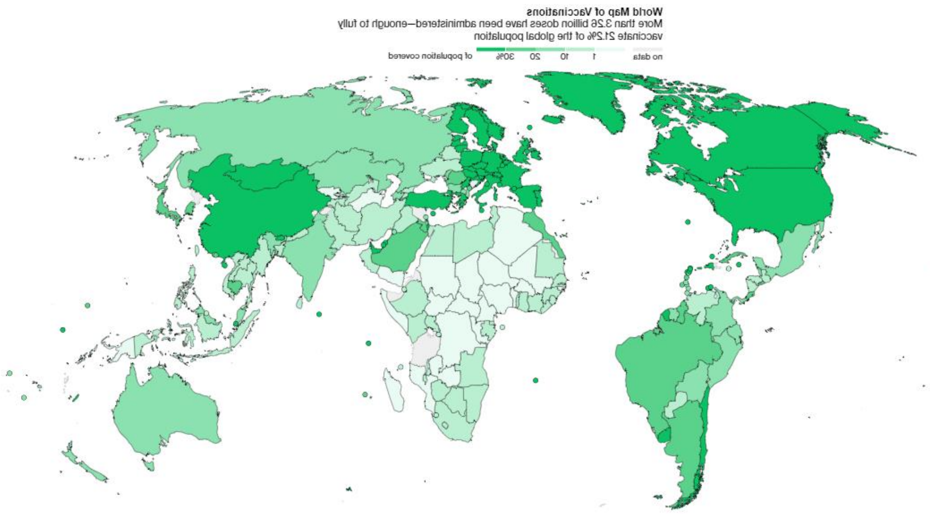

Figure 2: Covered population(7- 7-2021)

According to Bloomberg's vaccination tracker [12], more than 468 million COVID-19 doses had been provided in 135 countries as of June 24, 2021. With approximately 128 million portions, the United States leads the pack, accounting for 19.7% of the population of the country. 4.2 million people in Canada have been immunized. In India, 50 million people have been vaccinated, but Pakistan has only injected 325,000 doses. Inoculations have been given to 1.4 million people in Sweden and 771,000 persons in Norway. The negative effects of COVID-19 vaccines have been recorded in a few countries as well. Over 1200 side effect reports were reported to the Norwegian Medicine Agency on February 18, 2021 [13]. On 14 February 2021, two Swedish districts [14] suspended vaccination after receiving side effect reports. Following Norway, Denmark, and other Nordic and central European countries stopped providing AstraZeneca vaccines to their citizens in early March because of deaths caused by blood clotting as a side effect. People are frequently ready to share such news and personal encounters on social networking sites and form views about what they observe [15, 16]. While doing so, many people would reply and show various feelings [17, 18]. The study is inspired in such a way that such a tendency may spread quickly—social trends could convert into large meetings and rallies, which could eventually devolve into chaos, as seen in the Arab Spring. Sentiment analysis is an effective method for afterward inspecting opinions stated on social media, and timely study of public sentiment on social networking platforms could assist in averting such a situation [19, 20]. Deep neural networks, notably LSTM networks and their derivatives, have demonstrated promising results when used to extract sentiment polarity from the text [21]. Embedding pre-trained words like GloVe, FastText, and BERT improves task performance significantly. The creation and advancement of vaccines are critical to preventing the spread of COVID-19 and alleviating the huge clinical pressing concern. COVID-19 vaccines are being developed at a rapid pace by many pharmaceutical companies and universities [22]. There have been over 260 possible COVID19 vaccines developed, but only a few have been authorized. Some are in the later stages of the test [23]. Pfizer is the first multinational pharmaceutical company to receive approval for its vaccine in many nations. Currently, the COVID-19 vaccine is only available in limited quantities, with just about 6% of the world's population receiving doses.

The following are the two key questions we examine in this work about COVID-19 vaccinations, as well as our contributions to each question:

Which COVID-19 vaccine brands/makers have gotten the most attention recently? Do individuals lean toward any brands?

Concerning this, we investigated the sentiment of people situating in different countries towards various Coronavirus immunization brands. We physically resolved vaccine brands and relating keywords that are recently used mostly on the Twitter stage [24].

What individuals worry about the COVID-19 vaccination?

In this case, we identified the COVID-19 vaccine as the key source of worry among locals. We explored the well-known points using the deep learning model from the perspectives of time series, country, and feelings, respectively. In this research, we integrate the sentiments and opinions of users towards different vaccines. Sentiments and opinions will clarify the public response helping the health care authorities to analyze and better understand the public attitude and concerns regarding the Covid vaccine. Following are the main contributions in this study:

1) During the vaccination drive, two months of tweets on COVID-19 related hashtags were collected to examine sentiment polarity and feelings toward different vaccine brands. A classifier with a lexicon-based method is used to calculate the polarity of sentences/reviews.
2) 2) Aspect-based sentiment analysis is compared to certain state-of-the-art techniques in the suggested model.

The remaining part of the paper is laid out as follows: The previous investigations of sentiment analysis and decision support systems are described in Section 2. Section 3 depicts the proposed sentiment analysis conceptual paradigm. The experimental results, as well as a comparison to state-of-the-art procedures and a discussion, are presented in Section 4. Section 5 will include conclusions and recommendations for future work.

2 Related Work

Recent developments in sentiment analysis and sentiment computing will be considered text data for public opinion on financial markets [25], education [26,27], politics [28], etc.

To give just a few examples, various research studies also discuss people's reactions to it. Events are spoken on social media in general, especially on Twitter [29]. Event type Pandemics [30], protests [31], crime and terrorist attacks [32], Health-related events [33], natural disasters [34], etc. [35,36]. Coronavirus disease 2019 (COVID-19), also known as the coronavirus or COVID, is an infectious disease caused by coronavirus 2 and characterized by severe acute respiratory syndrome (SARS-CoV-2). In India, the immunization campaign to prevent COVID-19 started on January 16, 2021. Oxford-Covishield AstraZeneca's and Bharat Biotech's Covaxin were two vaccines used in this campaign. The study found that while the majority of people have good attitudes concerning vaccinations, there are also negative attitudes associated with negative emotions such as sadness and anger [37]. Acceptance of the COVID-19 vaccination is vital to the virus's eradication. The main target group for immunization in Pakistan is health care workers (HCWs). Their research focused on HCWs' acknowledgment of the COVID-19 vaccine and indicators of rejection. This is limited to 5,237 responses, but it can be modified to include more to increase its effectiveness [38]. The coronavirus disease (COVID-19) epidemic sparked widespread debate. Institutions, governments, and individuals can all benefit from understanding these debates as they try to navigate the pandemic. Data from Twitter was analyzed using machine learning techniques from the field of artificial intelligence.to April 2020, the study examined COVID-19 vaccines related discussions [39].

By crawling Twitter data with the terms 'Vaccine COVID-19,' Pristiyono et al. [40] do sentiment analysis using the Naive Bayes Algorithm. During the week, over 3.4 thousand negative tweets (56%) were measured, over 2.4 thousand positive tweets (39%) were measured, and the remaining 301 tweets (1%) were neutral. From April to August 2020, Garcia et al. [41] looked at Twitter posts in English and Portuguese, primarily from the United States and Brazil, in response to the COVID-19 pandemic. In both languages, 10 key subjects relevant to COVID-19 vaccinations were established, with seven topics being equivalent. One disadvantage of this method is the keywords used to gather content related to COVID-19.

Negative vaccine attitudes, as well as concern or refusal to receive immunizations, are significant hurdles to properly managing the COVID-19 pandemic in the long run. Saiful Islam et al. [42] examine predictors of four aspects of unfavorable vaccine attitudes in a large sample of UK individuals to identify those who are most likely to be uncertain about and refuse to receive the COVID-19 vaccine. In all, 14% of respondents stated they would refuse to take the COVID-19 vaccine, while 23% said they were undecided. In Bangladesh, Garcia et al. [43] investigated local knowledge, attitudes, and opinions concerning COVID-19 vaccines. The findings point to a lack of understanding but more favorable attitudes of the COVID-19 immunization among Bangladesh's general populace. Before implementing a mass vaccination program, education initiatives should be implemented to increase information and promote quick well-being.

Between April 11 and April 16, 2020, 16,000 tweets were analyzed to discover their associated moods and emotions. This study looked into the feelings and sentiments associated with terms like "Chinese virus," "Wuhan virus," and "Chinese coronavirus." The use of slurs and foul words was common. It explains why there has been an uptick in online harassment on Twitter. According to the statistics, a substantial number of customers are tweeting with usually negative opinions against ethnic Asians.

Vaccines are a useful tool, but they must be used correctly and in conjunction with other evidence-based public health programs, according to Jerome H. Kim et al., [46]. In addition to constant vaccination deployment, a complete preventative program, ongoing work on vaccine optimization, novel vaccines, correlates, long-term safety, and continued surveillance will be required. To understand the efficiency of herd immunity, systematic implementation of post-licensure research to determine the primary parameters surrounding herd immunity and the policies emerging from that information will be required. COVID-19 vaccinations that are both safe and efficacious were created in about 11 months. Furthermore, new scientific questions about vaccinations, such as vaccination regimen optimization, booster doses, correlates of protection, vaccine effectiveness, safety, and increased surveillance, need to be solved to improve vaccine efficacy. If these post-efficacy actions are accomplished in a timely and coordinated manner, the pandemic will be effectively and efficiently ended.

The breakthroughs in vaccine research and development, according to Tri Wibawa et al., [47], give our societies hope that we will be able to deal with the COVID-19 pandemic. The immediate demand for vaccine research speed must be balanced against the inherent necessity for research subject protection, which is at the heart of the research ethical dilemma. The ethical difficulties in COVID-19 vaccine research and development are identified and discussed in this narrative review, which all stakeholders should be aware of and evaluate.

3 Proposed Model

This section details the collection of tweets about COVID-19 vaccines during the second wave of the coronavirus. The sentiment analysis process in tweets from Pakistan, India, Norway, Sweden, the United States, and Canada is also outlined here.

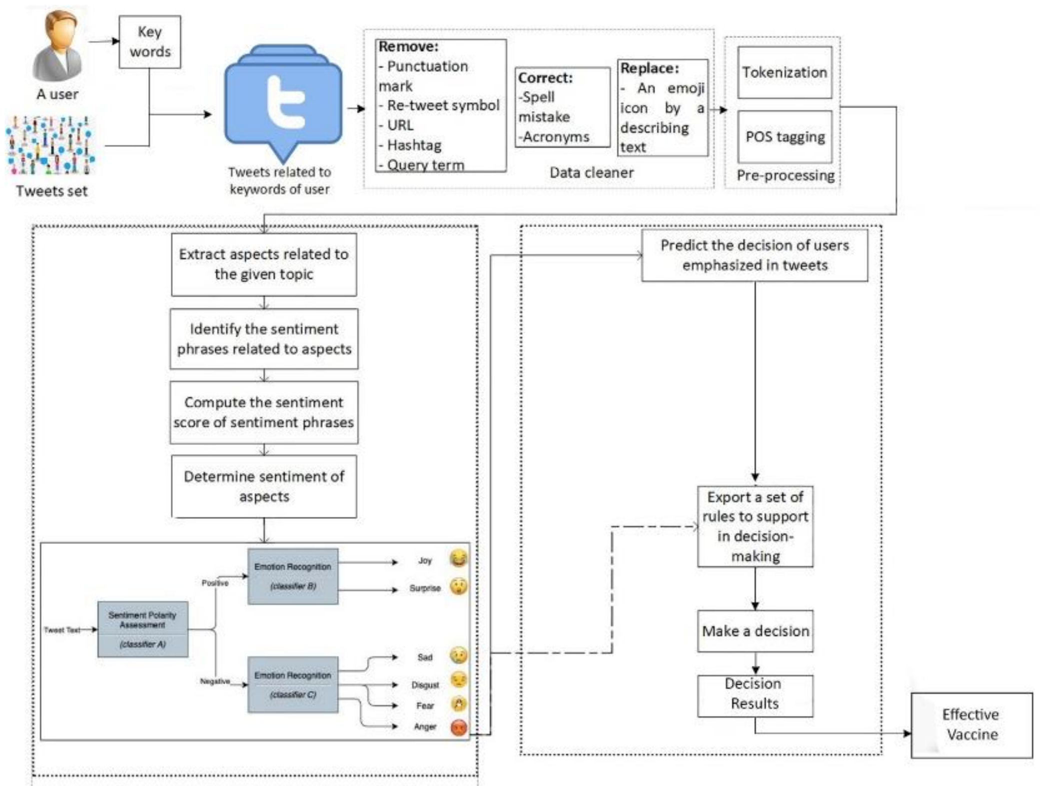

Figure 3: Proposed Methodology

A. Data Set

The data set [48] used in this study contains tweets from Twitter during the Covid-19's second intake for culturally diverse emotion recognition. For solid cross-cultural polarity measurement, six countries were chosen from three continents; two from each that share comparative culture. In Asia, India and Pakistan were chosen in Europe, Norway, Sweden, North America, Canada, and the United States. These six countries were chosen to look into the connection between the polarity shown during the first wave [49] and the second wave during the vaccination effort.

B. Data Collection

Tweepy, a Twitter Search API, was utilized to obtain the necessary data. We gathered data over time to investigate various people groups' viewpoints on COVID-19 immunization progress and the second wave. The terms were picked since they were directly relevant to the Covid-19 and have been trending on Twitter from the start.

C. Data Cleaning

The raw data collection was further processed to remove the emoji from the tweet text and clean it up. we extracted emoji from tweet text to help the sentiment analyzer produce correct findings. Emoji are a true depiction of a user's reaction/emotions in any literary composition. After cleansing the data, we needed to put together a list of words with semantic significance. For this reason, we fostered a tokenization function. All the content in the dataset was changed over into lowercase letters. Presently in this tokenization work, we had likewise taken out the stop words. Stop words are essentially the words that happen as often as possible in the tweets and have no meaning to the tweet. So we need to dispose of such words.

Eliminating these words also has the added benefit of speeding up the machine learning models. For the time being, our dataset was completely accurate and ready to be processed. Tweet id, date, language, cleaned text, emoticon, emotion score, subjectivity, polarity, userid, and country-code were all used to categorize each tweet. In the most recent informational gathering, there were 801,692 tweets from six countries. Table 1 shows the distribution of tweets by country.

Table 1. Country-wise tweets distribution

Country	December-2020	January-2021	February-2021	Total
United States	131,254	317,016	177,950	626,220
Canada	12,171	60,389	39,456	112,016
India	18,772	21,350	11,862	51,984
Norway	489	2481	143	3113
Pakistan	1147	2627	1612	5386
Sweden	688	1332	953	2973
Total	164,521	405,195	231,976	801,692

D. Tokenization & POS Tagging

Python's NLTK library includes a powerful sentence tokenizer and POS tagger. Python has a local tokenizer, the .splitx() function, which you can pass a separator and it will part the string that the function is approached on that separately. The NLTK tokenizer is stronger. It tokenizes a sentence into words and punctuation as shown in Figure 4.

```
import ntlk

tokens = ntlk.word_tokenize("Do you like this car?")

print("Tokens", tokens)

```

Figure 4: Python code for Tokenization

It will tokenize the sentence “Do you like this car?” as follows:
[‘Do’, ‘you’, ‘like’, ‘this’, ‘car’, ‘?’]

E. Classification Models

Figure 4 depicts the suggested categorization framework's abstract model. Long Short-Term Memory (LSTM) Networks [53], CNN and DNNs are used by all three classifiers (A, B, and C).

Table 2 shows the F1 and the precision scores on the test set - 10% of the dataset involving 160,000 tweets similarly partitioned into positive and negative polarities. The table presents the already best-announced precision and F1 score on the dataset, as reported in [54]. The model proposed in this article gives FastText outflanks any remaining models, including beforehand best-detailed precision. Accordingly, we pick this model as our first stage classifier to arrange tweets in certain and negative polarities

Table 2. Scores Accuracy

Model #	Model Name	F1 Score	Accuracy
1	DNN (Baseline)	79.0%	78.4%
2	**LSTM + FastText**	**82.4%**	**82.4%**
3	LSTM + GloVe	81.5%	81.4%
4	LSTM + GloVe Twitter	80.4%	80.4%
5	LSTM + w/o Pretrained Embed.	81.6%	81.4%
6	CONV Based on [28]	81.7%	81.1%

Our proposed model is written in Python, which is a very flexible language with a rich library ecosystem.

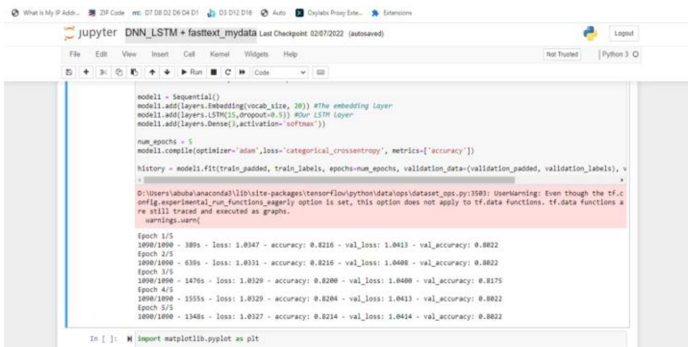

Figure 5. Python Execution

DNN (Deep Neural Network): The simplest sort of neural network is the DNN. It's a layered structure with an activation function that links all neurons on one layer to all neurons on the next. Although linked deep neural networks excel at processing text and other short sequences, their performance diminishes as the sequences grow longer. LSTM deep neural networks process current input while simultaneously maintaining prior states generated by earlier inputs to deal with lengthy sequences. LSTM can understand the word setting and hence outperforms DNN and other networks when processing extended sequences due to its capacity to remember earlier states.

Convolution Neural Network: In a CNN deep neural network, convolution and pooling are two important functions. To create a feature map that may be utilized for classification, the convolution method is applied to an input text or image with many channels of varied sizes. The pooling activity is sliding a two-dimensional filter across each channel of the convoluted feature guide, to sum up, features laying in sub-regions of the picture or text. CNN is more suited to image processing in general, although it has recently shown enough promise in sequence processing as well. The classifier A is trained using LSTM with pre-trained FastText [55] embedding on Sentximent140 [56], which comprises a total of 1.4 million tweets that are evenly transmitted between positive and negative sentiment polarity. Table 2 shows the findings of various models on the Sentiment140 data set. The model based on LSTM and pre-trained FastText outperforms all other models. Figure 6 shows a summary of the LSTM + FastText model.

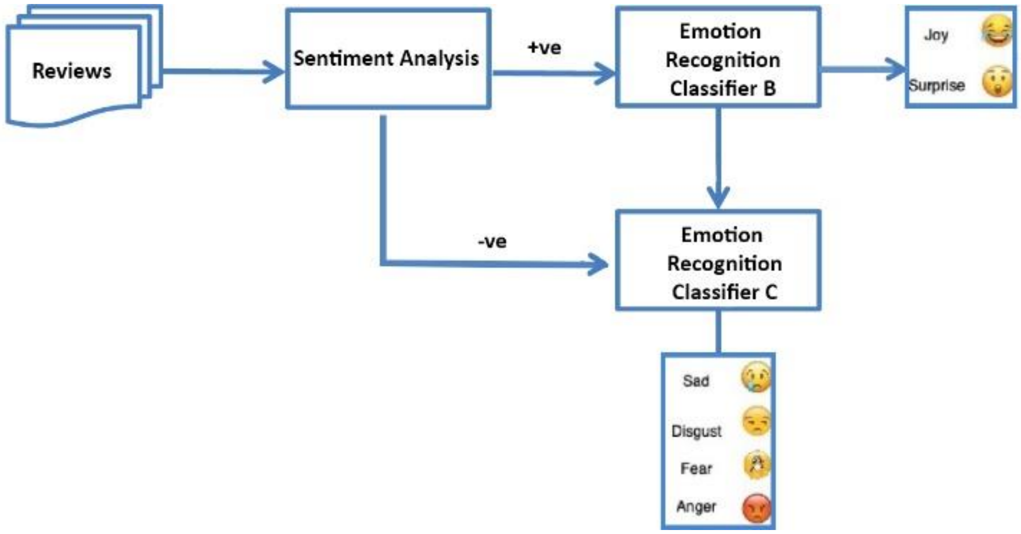

Figure 6: Abstract model for tweet classification.

F. Decision Support System

The decision issues are generally mind-boggling as they include the evaluation of items characterized by a few clashing rules [59, 60]. The proposed DSS makes the decision process more explicit, judicious, and efficient. The proposed model utilized the force of angle-based sentiment analysis frameworks as client inclinations to expand the decision force of decision support system DSS module utility functions to change the upsides of the domain credits into numerical values that address the client's level of satisfaction, taking into account his/her inclinations. We have considered one attribute i.e., percentage. On account of percentile attribute, it doesn't bother with any transformation, as they are now numbers. LSTM has the following features:

i. Long short-term memory is a type of RNN architecture that is mostly utilized for NLP.
ii. LSTM prioritizes feedback connections over feedforward connections, as opposed to normal feedforward neural networks. It analyses individual data points as well as data sequences as a whole.
iii. The embedding layer is the first layer, and 150 is the vocabulary size. After this, an LSTM layer was added with 128 units, afterwards, we add a dropout layer with dropping the 60% neurons. The LSTM and dropout layers were repeated three times. Lastly, a fully connected layer with three neurons with the activation function 'softmax' for predicting multiclass was added in the last layer.
iv. Categorical cross-entropy is the loss function used, and 'Adam' is the optimizer used, and we used 5 epochs to train our model.

The DSS model helps in decision-making using combining sentiment analysis for aspects with rules mined from LSTM + FastText. To implement this method, we consider five primary steps as we can see in

Figure 5. First, the input is given as total tweets, total negative, positive and neutral were extracted. Second, their percentage is calculated for each country concerning each vaccine. Next, we will get the user satisfaction degree for each vaccine. Finally, we will compare the percentage and consider the highest. The results of the experiments prove the efficiency of our proposal regarding the accuracy and gained information. Using the below equation, consider Percentage as P, Total Tweets as TT, Positive Tweets as PT, Extracted Tweets as ET, Negative Tweets as NT, Neutral Tweets as NeT.

$$\boldsymbol{P1 = Pt * \frac{100}{Tt}} \qquad \textbf{(1)}$$

$$\boldsymbol{P2 = Nt * \frac{100}{Tt}} \qquad \textbf{(2)}$$

$$\boldsymbol{P3 = Net * \frac{100}{Tt}} \qquad \textbf{(3)}$$

```
Start
INPUT value
Evaluate the percentage based on eq 1,2 and 3.
Calculate Results # P1 <-- PT x 100 / TT
Compare Results # P1 or P2 or P3
If Results > P1,P2,P3
    print Results
else goto Step 1
```

Figure 7: Algorithm of the proposed DSS model

4 Results and Discussion

All six countries are seeing an increase in the number of tweets about certain vaccines. Sentiment analysis of tweets directed at vaccination brands is shown in the tables below. From left to right, the names of vaccine brands, the number of tweets about the associated brand, the number of favorable, neutral, and negative among all tweets of this brand, and a comparison of sentiments toward different vaccinations are listed in the columns. Figure 8 depicts vaccination brands from several countries, along with doses and storage times.

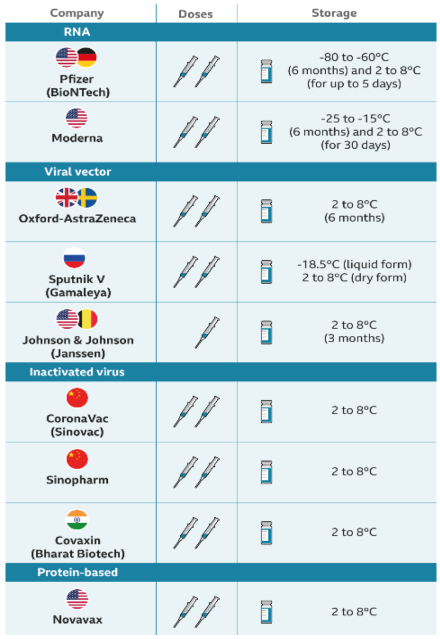

Figure 8: Comparison of different vaccine brands [33]

In Table 3. Sweden, we can see that the Pfizer brand has the highest number of tweets which is 1182 where the positive, negative, and neutral tweets are 701, 258, and 223 respectively. On the other hand, Novavax has 96 total tweets where 74 are positive 10 are neutral and 12 are negative. In Table 3, our decision support system shows the highest positive percentage of this brand, but we will also consider the total tweets ratio because people have reacted to Pfizer lesser than Novavax.

Table 3. Sweden

Vaccine Brand	Number of Tweets	Positive Tweets	Neutral Tweets	Negative Tweets
Sinopharm	9	5	0	4
Sinovac	12	8	2	2
Novavax	96	74	10	12
AstraZeneca	666	421	143	102
Johnson & Johnson	15	10	3	2
Sanofi	30	19	6	5
Moderna	128	81	35	12
Pfizer	1182	701	258	223
SputnikV	9	4	0	5
Valneva	9	5	4	0
CureVac	7	5	1	1

,

Table 4. Experimental results of DSS for Sweden

Vaccine Brand	Positive %	Neutral %	Negative %
Sinopharm	55.55%	0%	44.45%
Sinovac	66.66%	16.69%	16.65%
Novavax	70.08%	12%	17.92%
AstraZeneca	63.21%	28.81%	7.98%
Johnson & Johnson	69.54%	15.54%	14.92%
Saonfi	63.31%	23.31%	13.38%
Moderna	62.28%	23.34%	14.38%
Pfizer	59.30%	27.72%	12.98%
Sputnik V	44.45%	1.11%	54.44%
Valneva	55.56%	1.12%	43.32%
CureVac	71.56%	14.23%	14.21%

So, in Table 4. Experimental results of DSS for Sweden, positive sentiments about the Pfizer vaccine with the help of DSS is 59% positive and 12% negative rate. Most of the sentiments towards it were positive showing that people accept it more than other brands. Public about AstraZeneca also showed satisfactory sentiments having 63% positive sentiments and 7% negative sentiments. So, the healthcare authorities may consider both of them in Sweden.

Table 5. Pakistan

Vaccine Brand	Number of Tweets	Positive Tweets	Neutral Tweets	Negative Tweets
Sinopharm	69	65	0	4
Sinovac	712	278	272	222
Novavax	96	74	10	12
AstraZeneca	1666	1421	143	102
Johnson & Johnson	115	110	3	2
Sanofi	30	19	6	5
Moderna	128	81	35	12
Pfizer	1182	701	258	223
SputnikV	99	94	0	5
Valneva	9	5	4	0
CureVac	77	35	17	17

Table 6. Experimental results of DSS for Pakistan

Vaccine Brand	Positive %	Neutral %	Negative %
Sinopharm	94.20%	0.00%	5.80%
Sinovac	39.96%	18.46%	41.58%
Novavax	77.18%	14.14%	8.68%
AstraZeneca	83.28%	6.51%	10.21%
Johnson & Johnson	81.54%	10.57%	7.89%
Saonfi	57.31%	19.31%	23.38%
Moderna	63.21%	27.42%	9.37%
Pfizer	67.30%	21.82%	10.88%
Sputnik V	93.44%	0.00%	6.56%
Valneva	70.46%	29.54%	0.00%
CureVac	50.55%	25.55%	23.90%

In Table 5. Pakistan we can see most people have tweeted about AstraZeneca in Pakistan. In Table 6, our Decision Support System shows a higher response of sentiments about AstraZeneca having 83% acceptance. The positive tweets towards it were highest showing that people prefer it more than other brands in Pakistan. SputnikV and Sinopharm have the highest percentages (approximately 93 percent and 94 percent, respectively). But the total number of tweets was very smaller compared to AstraZeneca, so we can't consider these.

Table 7. Norway

Vaccine Brand	Number of Tweets	Positive Tweets	Neutral Tweets	Negative Tweets
Sinopharm	19	12	4	3
Sinovac	27	13	12	2
Novavax	148	86	45	17
AstraZeneca	497	219	137	141
Johnson & Johnson	177	85	57	35
Sanofi	50	32	9	9
Moderna	2386	1384	642	360
Pfizer	4535	2398	1214	923
SputnikV	17	6	4	7
CureVac	9	7	1	1

Table 8. Experimental results of DSS for Norway

Vaccine Brand	Positive %	Neutral %	Negative %
Sinopharm	63.80%	21.05%	15.15%
Sinovac	48.14%	44.44%	7.42%
Novavax	58.10%	36.40%	5.50%
AstraZeneca	44.06%	27.56%	28.88%
Johnson & Johnson	48.02%	32.20%	19.78%
Saonfi	45.31%	38.13%	16.56%
Moderna	58.00%	26.00%	16.00%
Pfizer	52.87%	26.76%	20.37%
Sputnik V	31.24%	25.59%	43.17%
Valneva	0.00%	0.00%	0.00%
CureVac	61.57%	22.22%	16.21%

In Table 7, the public of Norway has tweeted most towards Pfizer having 52% positivity and 20% negativity and the remaining was neutral. As Pfizer has most positive sentiments than any other vaccine brand but on the other hand, we can also see that Pfizer has the highest negative sentiments as compared to others. But this ratio is very small for the 4535 tweets. Table 8 shows Sinopharm has the highest positive percentage but the tweets are very small in number same goes for the CureVac vaccine brand which has a 61% positivity ratio having a total of 9 tweets. So, we can't consider these two brands of the vaccine because the tweets are very less in number as compared to Pfizer.

Table 9. USA

Vaccine Brand	Number of Tweets	Positive Tweets	Neutral Tweets	Negative Tweets
Sinopharm	219	212	4	3
Sinovac	27	13	12	2
Novavax	148	86	45	17
AstraZeneca	17497	219	17137	141
Johnson & Johnson	42177	42285	57	35
Sanofi	50	32	9	9
Moderna	2386	1384	642	360
Pfizer	444535	442398	1214	923
SputnikV	17	6	4	7
CureVac	9	7	1	1

Table 10. Experimental results of DSS in the USA

Vaccine Brand	Positive %	Neutral %	Negative %
Sinopharm	96.80%	1.84%	1.36%
Sinovac	48.14%	44.68%	7.18%
Novavax	58.10%	30.42%	11.48%
AstraZeneca	31.25%	40.95%	27.80%
Johnson & Johnson	98.56%	1.34%	0.10%
Saonfi	69.31%	18.45%	12.24%
Moderna	63.28%	23.35%	13.37%
Pfizer	99.11%	0.27%	0.62%
Sputnik V	35.29%	25.52%	39.19%
Valneva	0.00%	0.00%	0.00%
CureVac	56.57%	22.21%	21.22%

In Table 9, people have tweeted the highest about Pfizer in the US country which is 444535. This is high in number as compared to other brands. In Table 10, we can observe that Pfizer has a 99% positivity ratio and a 0.6% negativity ratio, which is not a thing for a very high number of tweets. Johnson & Johnson has the 2nd highest number of tweets i.e., 42177 with 98% positivity and 0.1% negativity ratio respectively. So, from both tables, it can be concluded that both Pfizer and Johnson & Johnson can be considered because the public believes these two vaccines generally are safe to use.

Table 11. Canada

Vaccine Brand	Number of Tweets	Positive Tweets	Neutral Tweets	Negative Tweets
Sinopharm	69	65	0	4
Sinovac	7712	278	272	222
Novavax	96	74	10	12
AstraZeneca	71666	71421	143	102
Johnson & Johnson	7115	6110	673	72
Sanofi	30	19	6	5
Moderna	128	81	35	12
Pfizer	11182	91701	1258	1223
SputnikV	99	94	0	5
Valneva	9	5	4	0
CureVac	11771	9935	2217	17

Table 12. Experimental results of DSS for Canada

Vaccine Brand	Positive %	Neutral %	Negative %
Sinopharm	94.21%	0.00%	5.79%
Sinovac	45.18%	34.43%	20.39%
Novavax	77.08%	10.45%	12.47%
AstraZeneca	99.06%	0.66%	0.28%
Johnson & Johnson	83.89%	9.45%	6.66%
Saonfi	56.33%	27.01%	16.66%
Moderna	63.28%	27.30%	9.42%
Pfizer	82.47%	10.70%	6.83%
Sputnik V	94.94%	0.00%	5.06%
Valneva	50.49%	44.45%	5.06%
CureVac	84.40%	14.03%	1.57%

Analyzing Table 11 and Table 12, Canadian people preferred AstraZeneca to have a 71666 total number of tweets which has a 99% positive ratio. Despite this, Canadians are eager to discuss immunization. The majority of Canadians have had no bad responses to vaccination and believe in it. As a result, citizens are concerned about government vaccination allotment, with the AstraZeneca brand receiving 99 percent approval and 0.2 percent rejection.

Table 13. India

Vaccine Brand	Number of Tweets	Positive Tweets	Neutral Tweets	Negative Tweets
Sinopharm	69	65	0	4
Sinovac	22712	12278	2272	8222
Novavax	96	74	10	12
AstraZeneca	31666	31421	143	102
Johnson & Johnson	115	110	3	2
Sanofi	30	19	6	5
Moderna	128	81	35	12
Pfizer	1182	701	258	223
SputnikV	99	94	0	5
Valneva	9	5	4	0
CureVac	77	35	17	17

Table 14. Experimental results of DSS for India

Vaccine Brand	**Positive %**	**Neutral %**	**Negative %**
Sinopharm	**94.49%**	**3.60%**	**1.91%**
Sinovac	**54.06%**	**10.00%**	**35.94%**
Novavax	**47.09%**	**35.96%**	**16.95%**
AstraZeneca	**99.23%**	**0.45%**	**0.32%**
Johnson & Johnson	**95.66%**	**2.60%**	**1.74%**
Saonfi	**62.23%**	**36.66%**	**1.11%**
Moderna	**64.43%**	**26.20%**	**9.37%**
Pfizer	**59.32%**	**21.82%**	**18.86%**
Sputnik V	**94.94%**	**0.00%**	**5.06%**
Valneva	**94.94%**	**5.06%**	**0.00%**
CureVac	**45.45%**	**27.28%**	**27.27%**

Table 13 shows Indian people are very positive about the AstraZeneca vaccine brand. Due to the new variant of the coronavirus, people begin to express positive and negative emotions. AstraZeneca has the lowest negative tweets which means that it is accepted most among the other brands and the public is showing positive emotions towards it. We can also see that negative tweet toward Sinovac is the highest in number, having a 35% negativity ratio which is high among other vaccine brands.

This research offers a far-reaching assessment of mentalities toward COVID-19 vaccination with the help of DSS, especially the job of vaccine credits, potential strategy mediations, and deception. A few past investigations have broken down the impacts of vaccination qualities on the ability to inoculate, yet the methodology is to measure readiness to acknowledge a nonexclusive COVID-19 vaccine.

Several volumes of research show, nevertheless, that vaccine preference relies on explicit immunization attributes [57,58]. Ongoing exploration thinking about the impact of traits like adequacy, side effects, and country of origin move toward seeing what properties mean for people's aims to vaccinate, however, proof about the qualities of real vaccines, banters about how to advance vaccination inside the populace, and inquiries regarding the impact of deception have moved rapidly. On the theoretical side, we plan to make the system multi-lingual, so that it can analyze reviews in other languages.

5 Conclusion

We looked at people's comments on Twitter during the recent Coronavirus outbreak to determine how they felt about the COVID-19 vaccine. Using DSS, we examined individual attitudes toward COVID-19 vaccination brands in various regions using a dataset of tweets. It was possible to conduct both qualitative and quantitative analysis. Public attitudes towards vaccines have greatly improved as a result of the rapid expansion of immunization in many countries, but a significant number of people are still opposed to them. It may be possible to improve the accuracy of the proposed model by using text processing techniques such as unique transformers and attention-based approaches. The use of contextual word embedding techniques like BERT, Elmo, and others should have been evaluated for their applicability to sentiment and emotion analysis in social media writing. Our study focused on tweets, but other social media sites like Facebook, Instagram, and others may also be investigated to find out more about people's opinions on COVID-19 and its inoculation cycle. According to the old saying, "a picture is worth a thousand words." With an updated expert system, processing photographs for extracting individuals' attitudes and feelings could be considered another aspect of this study in the future.

References

[1] N. Zhu, D. Zhang, W. Wang, X. Li, B. Yang, J. Song, X. Zhao, B. Huang, W. Shi, R. Lu et al., “A novel coronavirus from patients with pneumonia in china, 2019,” New England journal of medicine, 2020.

[2] Rana, M. R. R., Nawaz, A., & Iqbal, J. (2018). A survey on sentiment classification algorithms, challenges, and applications. Acta Universities Sapientiae, Informatica, 10(1), 58-72.

[3] https://www.nationalgeographic.com/science/graphics/mapping-coronavirus-infections-across-the-globe.

[4] https://www.aljazeera.com/news/2021/3/10/uk-covid-19-variant-30-100-more-deadly-study-finds.

[5] Pfefferbaum, B.; North, C.S. Mental health and the Covid-19 pandemic. N. Engl. J. Med. 2020, 383, 510–512.

[6] Imran, A.S.; Daudpota, S.M.; Kastrati, Z.; Batra, R. Cross-cultural polarity and emotion detection using sentiment analysis and deep learning on COVID-19 related tweets. IEEE Access 2020, 8, 181074–181090.

[7] H. Tufail, M. U. Ashraf, K. Alsubhi and H. M. Aljahdali, "The Effect of Fake Reviews on e-Commerce During and After Covid-19 Pandemic: SKL-Based Fake Reviews Detection," in IEEE Access, vol. 10, pp. 25555-25564, 2022, doi: 10.1109/ACCESS.2022.3152806.

[8] F. Es-Sabery et al., "A MapReduce Opinion Mining for COVID-19-Related Tweets Classification Using Enhanced ID3 Decision Tree Classifier," in IEEE Access, vol. 9, pp. 58706-58739, 2021, doi: 10.1109/ACCESS.2021.3073215.

[9] Chintalapudi, Nalini, Gopi Battineni, and Francesco Amenta. "Sentimental analysis of COVID-19 tweets using deep learning models." Infectious Disease Reports 13, no. 2 (2021): 329-339.

[10] H. Silva, E. Andrade, D. Araujo and J. Dantas, "Sentiment Analysis of Tweets Related to SUS Before and During COVID-19 pandemic," in IEEE Latin America Transactions, vol. 20, no. 1, pp. 6-13, Jan. 2022, doi: 10.1109/TLA.2022.9662168.

[11] Luo, Yi, and Xiaowei Xu. "Comparative study of deep learning models for analyzing online restaurant reviews in the era of the COVID-19 pandemic." International Journal of Hospitality Management 94 (2021): 102849.

[12] https://www.bloomberg.com/graphics/ covid-vaccine-tracker-global-distribution/

[13] https://tinyurl.com/db2x86j7

[14] https://tinyurl.com/2empedan

[15] L. H. X. Ng and J. Y. Loke, "Analyzing Public Opinion and Misinformation in a COVID-19 Telegram Group Chat," in IEEE Internet Computing, vol. 25, no. 2, pp. 84-91, 1 March-April 2021, doi: 10.1109/MIC.2020.3040516.

[16] Ghasiya, Piyush, and Koji Okamura. "Investigating covid-19 news across four nations: A topic modeling and sentiment analysis approach." Ieee Access 9 (2021): 36645-36656.

[17] X. Yu, M. D. Ferreira and F. V. Paulovich, "Senti-COVID19: An Interactive Visual Analytics System for Detecting Public Sentiment and Insights Regarding COVID-19 From Social Media," in IEEE Access, vol. 9, pp. 126684-126697, 2021, doi: 10.1109/ACCESS.2021.3111833.

[18] T. Da and L. Yang, "Local COVID-19 Severity and Social Media Responses: Evidence From China," in IEEE Access, vol. 8, pp. 204684-204694, 2020, doi: 10.1109/ACCESS.2020.3037248.

[19] H. Jelodar, Y. Wang, R. Orji and S. Huang, "Deep Sentiment Classification and Topic Discovery on Novel Coronavirus or COVID-19 Online Discussions: NLP Using LSTM Recurrent Neural Network Approach," in IEEE Journal of Biomedical and Health Informatics, vol. 24, no. 10, pp. 2733-2742, Oct. 2020, doi: 10.1109/JBHI.2020.3001216.

[20] L. -A. Cotfas, C. Delcea, I. Roxin, C. Ioanaş, D. S. Gherai and F. Tajariol, "The Longest Month: Analyzing COVID-19 Vaccination Opinions Dynamics From Tweets in the Month Following the First Vaccine Announcement," in IEEE Access, vol. 9, pp. 33203-33223, 2021, doi: 10.1109/ACCESS.2021.3059821.

[21] Kaur, Harleen, Shafqat Ul Ahsaan, Bhavya Alankar, and Victor Chang. "A proposed sentiment analysis deep learning algorithm for analyzing COVID-19 tweets." Information Systems Frontiers 23, no. 6 (2021): 1417-1429.

[22] A. Baj-Rogowska, "Mapping of the Covid-19 Vaccine Uptake Determinants From Mining Twitter Data," in IEEE Access, vol. 9, pp. 134929-134944, 2021, doi: 10.1109/ACCESS.2021.3115554.

[23] WHO (2021). The covid-19 candidate vaccine landscape. Accessed: March 20, 2021. [Online]. Available: https://www.who.int/publications/m/item/draft-landscape-of-covid-19-candidate-vaccines.

[24] U. Naseem, I. Razzak, M. Khushi, P. W. Eklund and J. Kim, "COVIDSenti: A Large-Scale Benchmark Twitter Data Set for COVID-19 Sentiment Analysis," in IEEE Transactions on Computational Social Systems, vol. 8, no. 4, pp. 1003-1015, Aug. 2021, doi: 10.1109/TCSS.2021.3051189.

[25] Carosia, A.; Coelho, G.P.; Silva, A. Analyzing the Brazilian financial market through Portuguese sentiment analysis in social media. Appl. Artif. Intell. 2020, 34, 1–19.

[26] Chauhan, P.; Sharma, N.; Sikka, G. The emergence of social media data and sentiment analysis in election prediction. J. Ambient. Intell. Humaniz. Comput. 2021, 12, 2601–2627.

[27] Kastrati, Z.; Imran, A.S.; Kurti, A. Weakly supervised framework for aspect-based sentiment analysis on students' reviews of MOOCs. IEEE Access 2020, 8, 106799–106810.

[28] Kastrati, Z.; Dalipi, F.; Imran, A.S.; Pireva Nuci, K.; Wani, M.A. Sentiment Analysis of Students' Feedback with NLP and Deep Learning: A Systematic Mapping Study. Appl. Sci. 2021, 11, 3986.

[29] Rajmohan, Akshay, Akash Ravi, K. O. Aakash, K. Adarsh, Anjuna D. Raj, and T. Anjali. "Cov2ex: a covid-19 website with region-wise sentiment classification using the top trending social media keywords." In 2021 Sixth International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET), pp. 113-117. IEEE, 2021.

[30] Xiang, X.; Lu, X.; Halavanau, A.; Xue, J.; Sun, Y.; Lai, P.H.L.; Wu, Z. Modern senicide in the face of a pandemic: An examination of public discourse and sentiment about older adults and COVID-19 using machine learning. J. Gerontol. Ser. B 2021, 76, e190–e200.

[31] Won, D.; Steinert-Threlkeld, Z.C.; Joo, J. Protest activity detection and perceived violence estimation from social media images. In Proceedings of the 25th ACM International Conference on Multimedia, Mountain View, CA, USA, 23–27 October 2017; pp. 786–794

[32] Burnap, P.; Williams, M.L.; Sloan, L.; Rana, O.; Housley, W.; Edwards, A.; Knight, V.; Procter, R.; Voss, A. Tweeting the terror: modeling the social media reaction to the Woolwich terrorist attack. Soc. Netw. Anal. Min. 2014, 4, 206.

[33] Reynard, D.; Shirgaokar, M. Harnessing the power of machine learning: Can Twitter data be useful in guiding resource allocation decisions during a natural disaster? Transp. Res. Part D Transp. Environ. 2019, 77, 449–463.

[34] Gohil, S.; Vuik, S.; Darzi, A. Sentiment analysis of health care tweets: a review of the methods used. JMIR Public Health Surveill. 2018, 4, e43.

[35] Dunkel, A.; Andrienko, G.; Andrienko, N.; Burghardt, D.; Hauthal, E.; Purves, R. A conceptual framework for studying collective reactions to events in location-based social media. Int. J. Geogr. Inf. Sci. 2019, 33, 780–804.

[36] Kumar, A.; Jaiswal, A. Systematic literature review of sentiment analysis on Twitter using soft computing techniques. Concurr. Comput. Pract. Exp. 2020, 32, e5107.

[37] Dubey, A. D. (2021). Public Sentiment Analysis of COVID-19 Vaccination Drive in India. Available at SSRN 3772401.

[38] Malik, A., Malik, J., & Ishaq, U. (2021). Acceptance of COVID-19 Vaccine in Pakistan Among Health Care Workers. medRxiv.

[39] Hung, M., Lauren, E., Hon, E. S., Birmingham, W. C., Xu, J., Su, S., ... & Lipsky, M. S. (2020). Social network

analysis of COVID-19 Sentiments: application of artificial intelligence. Journal of medical Internet research, 22(8), e22590

[40] Ritonga, M., Al Ihsan, M. A., Anjar, A., & Rambe, F. H. (2021, February). Sentiment analysis of COVID-19 vaccine in Indonesia using Naïve Bayes Algorithm. In IOP Conference Series: Materials Science and Engineering (Vol. 1088, No. 1, p. 012045). IOP Publishing.

[41] Garcia, K., & Berton, L. (2021). Topic detection and sentiment analysis in Twitter content related to COVID-19 from Brazil and the USA. Applied Soft Computing, 101, 107057.

[42] Islam, M. S., Siddique, A. B., Akter, R., Tasnim, R., Sujan, M. S. H., Ward, P. R., & Sikder, M. T. (2021). Knowledge, attitudes, and perceptions towards COVID-19 vaccinations: a cross-sectional community survey in Bangladesh. medRxiv.

[43] Verger, P., Scronias, D., Dauby, N., Adedzi, K. A., Gobert, C., Bergeat, M., ... & Dubé, E. (2021). Attitudes of healthcare workers towards COVID-19 vaccination: A survey in France and French-speaking parts of Belgium and Canada, 2020. Eurosurveillance, 26(3), 2002047.

[44] M. Ramzan, “Are Tweets The Real Estimators Of Election Results?” 2017, no. August, pp.

[45] Dubey, Akash Dutt. 2020. “The Resurgence of Cyber Racism during the COVID-19 Pandemic and Its Aftereffects: Analysis of Sentiments and Emotions in Tweets.” *JMIR Public Health and Surveillance* 6(4):1–7. DOI: 10.2196/19833.

[46] Ishaq, A., Asghar, S., & Gillani, S. A. (2020). Aspect-based sentiment analysis using a hybridized approach based on CNN and GA. IEEE Access, 8, 135499-135512.

[47] Chang, V., Liu, L., Xu, Q., Li, T., & Hsu, C. H. (2020). An improved model for sentiment analysis on luxury hotel review. Expert Systems, e12580.

[48] Nandal, N., Tanwar, R., & Pruthi, J. (2020). Machine learning-based aspect-level sentiment analysis for Amazon products. Spatial Information Research, 28(5), 601-607.

[49] Alamanda, M. S. (2020). Aspect-based sentiment analysis search engine for social media data. CSI Transactions on ICT, 8, 193-197.

[50] Tran, T., Ba, H., & Huynh, V. N. (2019, March). Measuring hotel review sentiment: An aspect-based sentiment analysis approach. In International Symposium on Integrated Uncertainty in Knowledge Modelling and Decision Making (pp. 393-405). Springer, Cham.

[51] Luu, T.J.P.; Follmann, R. The Relationship between Sentiment Score and COVID-19 Cases in the USA 2020. Available online: https://jackluu.io/files/LuuResearchPaper.pdf (accessed on 29 March 2021).

[52] Papathanasiou, J., Ploskas, N., & Linden, I. (Eds.). (2016). Real-World Decision Support Systems: Case Studies (Vol. 37). Springer.

[53] https://docs.oracle.com/javase/8/docs/api/java/util/stream/Stream.html

[54] https://www.drupal.org/project/search_api

[55] https://www.nltk.org

[56] Basiri, Mohammad Ehsan, Shahla Nemati, Moloud Abdar, Somayeh Asadi, and U. Rajendra Acharrya. "A novel fusion-based deep learning model for sentiment analysis of COVID-19 tweets." Knowledge-Based Systems 228

(2021): 107242.

[57] Go, A.; Bhayani, R.; Huang, L. Twitter Sentiment Classification Using Distant Supervision. Available online: https://www-stanford.edu/people/alecmgo/papers/TwitterDistantSupervision09.pdf (accessed on 26 March 2021).

[58] https://www.bbc.com/news/world-africa-56992121

[59] Muhammad Rizwan Rashid Rana, Saif Ur Rehman, Asif Nawaz,, Tariq Ali , Munir Ahmed, “A Conceptual Model for Decision Support Systems Using Aspect Based Sentiment Analysis”, Proceedings of the Romanian Academy, Series A, of the Romanian Academy Volume 22, Number 4/2021, pp. 381–39

[60] M.Fahim, Saif ur Rehman, Yasir Malik and Dr. Sohail Asghar "Multi Agent Based Decision Support System For Prioritized Emergency Fire Evacuation", Published In New Trends in Information Science and Service Science (NISS), 2010 4th International Conference on Issue Date 11-13 May 2010.On page(s): 457 - 463, Location Gyeongju, Korea