Annals of R.S.C.B., ISSN:1583-6258, Vol. 25, Issue 4, 2021, Pages. 2851 – 2863
Received 05 March 2021; Accepted 01 April 2021.

Global Analysis of COVID-19 and its Impact

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ABSTRACT

We are in the midst of an unprecedented time. The ongoing health crisis severely impacts all major international countries due to the COVID-19 pandemic. This paper is an effort to gain valuable insights into the pandemic and its aftermath. The main focus is to analyze the spread pattern of this virus all over the world by performing a comprehensive analysis and visualization of the cumulative data gathered through various sources. Through an in-depth review of scientific articles and surveys, the significant impact of COVID-19 across various sectors like education and economy has been listed. The way people used social media since the pandemic has changed significantly. Governments and municipalities need to know how their residents are reacting to changing circumstances and events, so we use sentiment analysis on Twitter data to help them.

KEYWORDS

COVID19, Analysis, Economy, Education, Visualization, Sentiment Analysis.

Introduction

The first human coronaviruses (HCoV) that cause respiratory tract plot contamination were presented by the revelation of HCoV-229E and HCoV-OC43 [1]. To date, there have been reports of numerous outbreaks. A pneumonia incident was recorded in Wuhan, China, in December 2019, and it has been associated to another strain of HCoV. As of March 22nd, 2021, 122,992,844 confirmed cases and 2,711,071 deaths, and 397,950,709 vaccine doses have been reported to WHO from various places in the world [4]. A comprehensive analysis and visualization of data from the Johns Hopkins database (time series) have been followed to get valuable insights into the pandemic. The top ten nations with the most extreme number of cases are the USA, the UK, France, Spain, Germany, Italy, Iran, China, Switzerland and Turkey.

Social distancing measures, travel bans, self-quarantine, and business closures change the very texture of social orders around the world. Some powerful approaches yield critical changes in the pattern of cases. China, Italy, and Spain have implemented a lockout policy (the impact saw after certain days). Closure of all minor organizations in Hubei (the effect was seen after five days), a joint agreement in South Korea, and a reduction in working hours in Iran [1]. India has managed to control the growth rate through some strict measures. According to reports, nationwide lockdowns were used to limit the growth of infected cases; however, some uncontrolled mass level occasions had adversely affected the infected cases [3].

The global education institutions are concerned about the Coronavirus Disease (COVID-19) pandemic. Attempts to keep the infection under control and deter its spread resulted in the unscheduled shutdown of schools in a number of countries around the world. The COVID-19's Educational Impact is investigated in this paper [10]. The repercussions of the COVID-19 pandemic keep creating articulated changes in teaching and learning practices for all education levels. This investigation presents the current circumstance of coronavirus spread all around the world alongside the effect and different measures taken to manage it. We also implement a Twitter sentiment analysis model that would help get an idea about the views of the people in regard to COVID19 vaccines.

Literature Review

We began our project by reviewing the existing research and review work. Majid Alizadeh et al. [1] carried out an in-depth analysis on the study of cases in major countries that include China, South Korea, the US, Italy, Spain, Iran, Japan and Germany using "Best Linear Regression".

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S. Udhaya Kumar et al. [2] discussed the outbreak in India with the impact on the economy with preparatory and preventive measures to be undertaken.
Rajan Gupta et al. [3] have discussed the use of exponential and polynomial regression modeling to predict cases. They also analyze and address the impact of the lockdown, social distancing measures, and mass events.

Sarvam Mittal [5] closely analyses the recorded cases. The researcher has drawn a statistical model for a deeper comprehension of COVID19 spread throughout India. The study's findings divulge the effects of COVID-19 in India.

FURQAN RUSTAM et al. [6] used machine learning algorithms to estimate the number of patients affected by COVID-19 in the future. The study results prove it is a good mechanism to use these methods for the current scenario of the COVID-19 pandemic.

Onyema et al. [10] provide the impact of COVID-19 on education. They gathered information from 200 people using a questionnaire survey. Learning disruptions, reduced accessibility to schooling and research services, job shortages, and increased educational loans are examples of the negative impacts on education.

Anis Koubaa [11] contributes by offering quantitative and statistical models that provide insights into the effects of COVID-19. It is recognized as one of the first systematic analytical papers on COVID-19.

Analysis

A. Dataset and Resources

The pandemic has infected people in 181 countries. Exploratory data analysis of active cases, confirmed cases, recovered cases and deaths due to COVID-19 are performed. "The dataset we've acquired is from the Johns Hopkins University's Center for Systems Science and Engineerings GitHub repository" [6]. The dataset includes recovered cases, confirmed cases and deaths. This data is updated daily. From the given data, we have calculated the number of active cases.

B. Methodology

It's essential to review and analyze the growth of this pandemic. The count of COVID-19 cases, including their geo-locations, can facilitate tracking the pandemic's spread and the patient distribution [7]. In this paper, we have performed an exploratory data analysis of the collected information. Our methodology comprises making descriptive models of the Coronavirus outbreak utilizing statistical charts to comprehend the nature of the spread and its impact [3]. The EDA goes through the cycle of data collection, cleaning & standardization, analyzing fundamental sections utilizing scripting, inferring new segments, and picturing the information in the graphical arrangement as described in Fig.1. In this paper, we use 'Python' for information handling, and from the dataset, we extract and process the data using the 'pandas' library. The 'Plotly' module was used to generate interactive graphs for improved visualization. We have developed our analysis of confirmed cases, active cases, deaths, and recovered cases globally. The descriptive model provides differing statistical charts, including bar charts, line charts, geographic maps, and heat maps to represent different features of the COVID-19 outbreak.

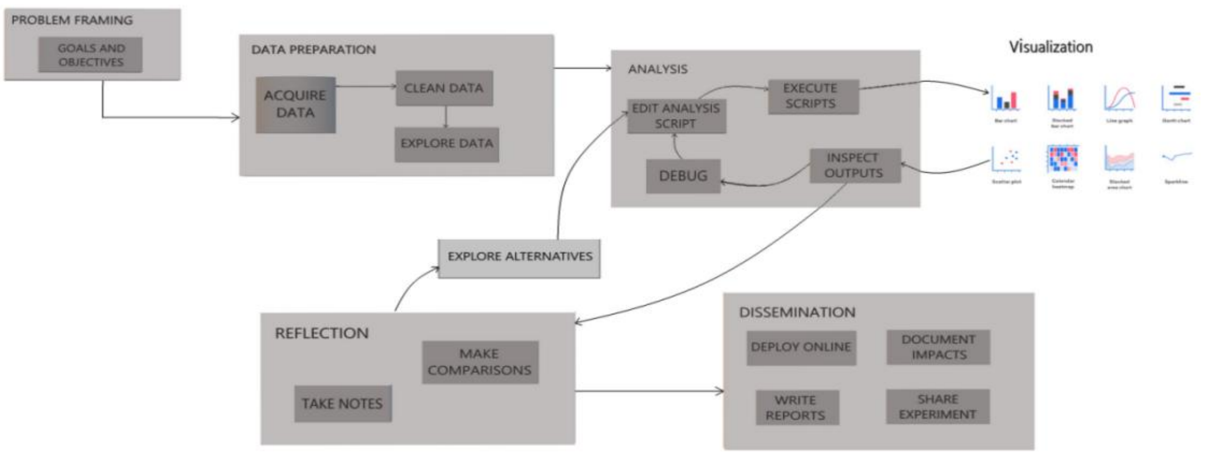

Fig. 1. Workflow Diagram of Data Analysis and Visualization

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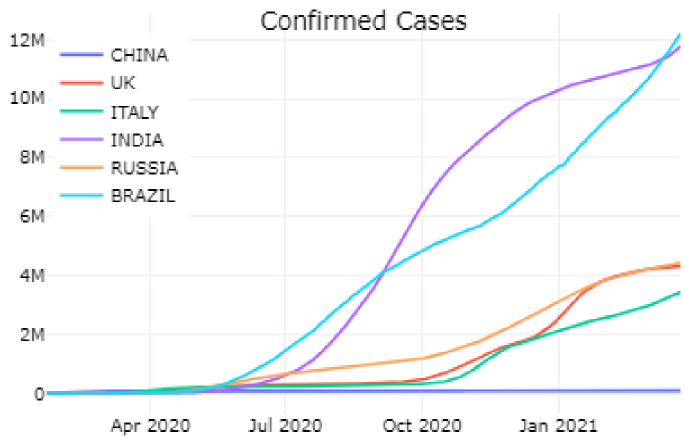
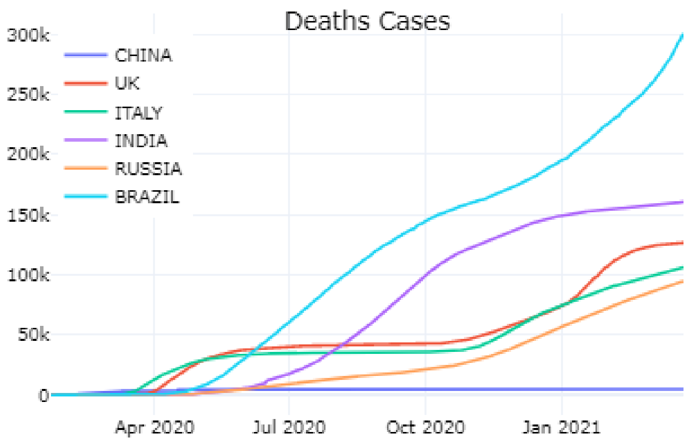
C. Spread of COVID-19 in China, Italy, UK, Russia, India, Brazil

Fig. 2 investigates the case trends in China, Italy, UK, Russia, India and Brazil. China showed development in the number of cases from January to mid-February; however, the count has been stable since. India observed a rise in confirmed cases from May onwards. Although it has the most confirmed cases in the group, as seen in Fig. 2a, there has been a fast recovery from June 2020 onwards, as observed in Fig. 2c. Confirmed cases in Italy and UK almost follow the same trend, with nearly two million cases registered around January 2021. Fig. 2c depicts a very slow recovery rate for the UK; as a result, it has the highest active cases in the group. Russia has managed to control the cases across all domains with a low death and active cases rate. Brazil started with many infected cases but has shown good recovery and currently has fewer active cases.



(a)



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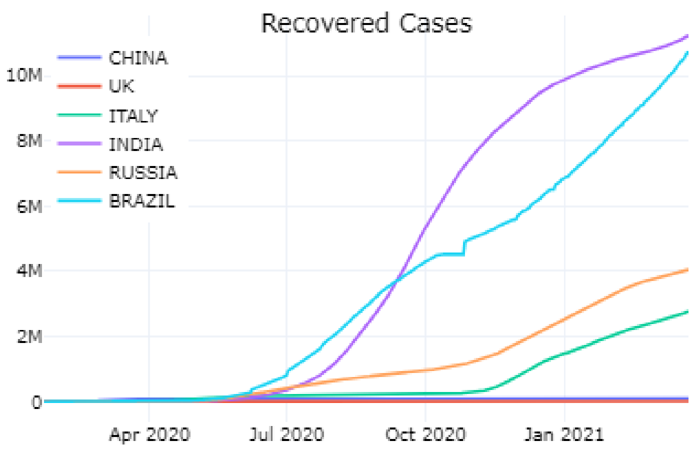

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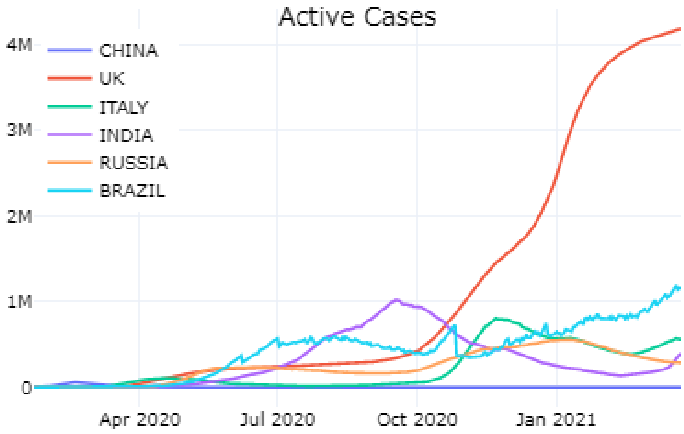
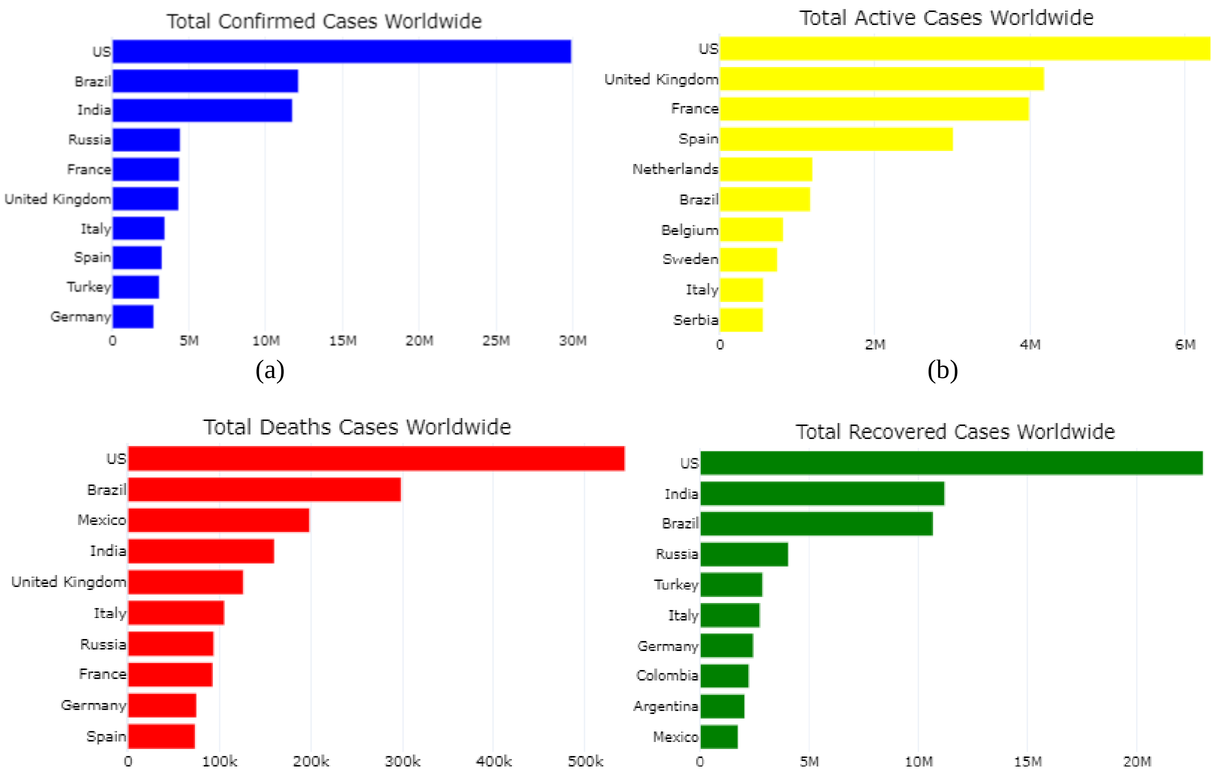


(d)

Fig. 2. Evolution of Cases in China, UK, Italy, India, Russia and Brazil: (a) Confirmed Cases, (b) Death Cases, (c) Recovered Cases, (d) Active Cases

D. Analysis of Top 10 Countries

During the early stages, investigations done till April 15th, 2020, show that China, Italy and the USA had the most cases. Fig 3. Describes ten countries sorted according to the most number of cases in each section – confirmed, recovered, deaths, and active cases as of March 2021. The USA leads in the number of confirmed, recovered, active cases, and deaths worldwide. Although India comes in third concerning confirmed cases, it has the most number of recovered cases and fewer deaths. It must be noted that China being the epicenter of the pandemic and among the most COVID19 confirmed cases in April, has recovered quickly and is not present in Fig 3. Russia and Turkey have controlled the spread of the virus. They have more recovered cases and fewer deaths, as seen in Figs 3(b) and 3(c). Although Spain has fewer confirmed cases, the slow recovery rate has put it at the 4th position with respect to active cases.



(c) (d)

Fig. 3. The top 10 Countries Ranked with most: (a) Confirmed Cases, (b) Active Cases, (c) Deaths, (d) Recovered Cases

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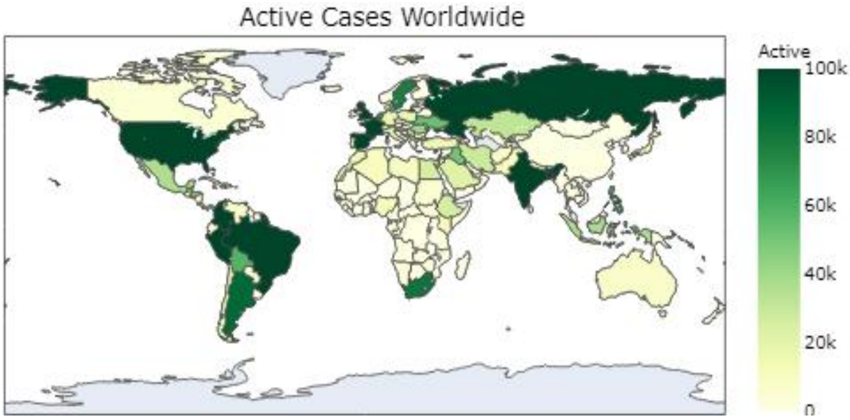
E. Heatmap

Heatmaps represent continuous data on a map using a color spectrum, usually used to identify a pattern or hot spots. Our heatmap described in Fig 4. gives a visual portrayal of the pandemic's effect alongside key perceptions to investigate nations. The analysis of cases of the top 10 countries (Fig 3) can be compared with the heatmaps, where these countries are marked with a darker shade of color. We created a heat map to showcase the progression of cases around the world from January-2020 to March-2021. Fig. 4 showcases the spread of the virus across all continents. By performing geospatial analysis, we tracked the growth of the pandemic. It was found that the virus spread from the East toward the West. Since the origin of the virus in China toward the end of January, Italy (South of Europe) toward the end of February, and afterward, it arrived in the USA [3].

(a)



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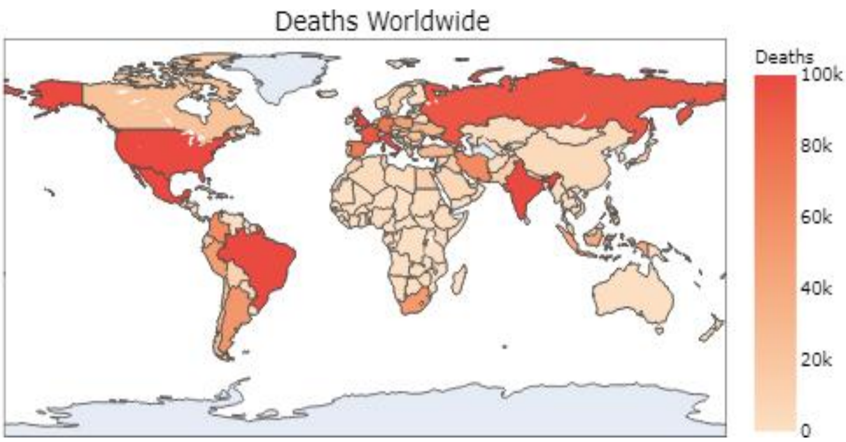

(c)

(d)

Fig. 4. Heatmap for the Spread of COVID19: (a) Confirmed Cases, (b) Active Cases, (c) Deaths, (d) Recovered Cases

F. Global Analysis on the Spread of COVID-19

Fig. 5 shows the global confirmed, deaths, recovered and active cases trend for COVID-19 from January 22nd, 2020 to March 22nd, 2021. From April 2020 onwards, the spread increased. The number of deaths is comparatively very less compared to the confirmed cases. The number of active cases is more compared to recovered cases. The number of new confirmed cases rose significantly during December 2020 and January 2021, which can be observed in Fig-5 due to mutated virus infections. It is reported that these new strains have enabled the virus to spread at a faster rate.

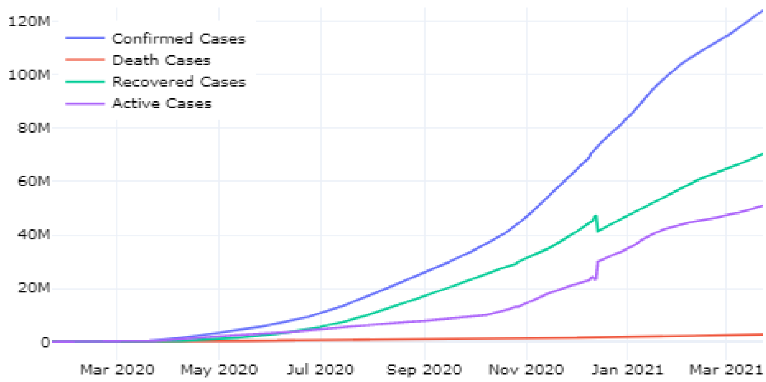

Fig. 5. Evolution of Cases Worldwide

Impact

G. Economy

For the effective containment of the disease, a country needs to stop its normal functioning, directly impacting the economy. To "flatten the curve" of the pandemic, governments all around the globe turned to lockdowns. This implied restraining millions of people at their residences, putting a halt to all commercial activity, and company closures. Fears of a severe and protracted global recession have emerged as a result of this. "The coronavirus recession is an economic crisis that hit the global economy in 2020 as a consequence of the pandemic". The effect of the COVID-19 on economies around the world is relatively ruinous, according to GDP figures for the second quarter of 2020. India's second-quarter reports were published, showing that its economy shrank by a non-annualized 25.2% (23.9% according to its statistics). Between January and March, China's economy shrank by 6.8%. (counted as -9.8% in official OECD figures) [13]. COVID-19-related problems in the United States have resulted in millions of people applying for unemployment insurance. The IMF has estimated the global economy to grow at -4.9 percent in 2020 as of June 2020. Global economic activity has been harmed as a result of the decrease in tourism. Oil prices dropped even lower in March because countries imposed lockdowns, affecting the transportation sector, accounting for 60% of the oil market. The longer this crisis continues, tougher it would be for businesses to remain stable. It may harm the production in the majority of domestic sectors. This successively has spill-over impacts on consumption, income, employment, and investment, slamming the breaks on the economy's total development pace. At this stage, the possible duration of the presently occurring health crisis remains uncertain. Therefore, it is troublesome to comprehend the extent of the world economy's damage completely.

H. Education

As a result of the pandemic, all school activities were halted. Schools and colleges launched online courses, which are in full swing. However, whether this study can ensure the learning result is still in doubt [8]. Students and teachers had to adjust to online learning and teaching because the campuses were shut down. College closures have a high educational, social and economical impact, and also the disruptions they cause touch people across communities; however, their impact is especially severe for underprivileged people and their families (UNESCO, 2020b). From the various changes in the educational sector, people can see the pandemic's impact on the educational situation of the world.

It is not a mystery that global travel was a key factor in spreading the infectious disease. This led to debates and rumination on student mobility in the near future. Various findings have highlighted the challenges the higher education community face within the international context. Findings suggest that COVID-19 has had a significant impact on the choice of 48.46% of students who had planned to study abroad in the recent past. Non-STEM scholars, on the other hand, have re-evaluated their decision to seek higher education outside of India [9].

According to UNESCO (2020b), the following are some of the negative consequences of school closures due to coronavirus:

1. Interruption in learning: Colleges provide vital skills, and students have been deprived of resources for growth and advancement since they have been closed.
2. Nutrition: Several children depend on school-provided meals for nutrition and food. Owing to school closures, this was jeopardized.
3. Unequal access to remote learning portals: Inability to resume learning due to a lack of infrastructure or good internet service through school closures.
4. Social Isolation: School closures robbed the youth and children of certain social communications and socialization that are important to learning, growth, and imagination, given that educational institutions are places for social activity and human interactions.

Sentiment Analysis

A. Methodology

We implement a Twitter sentiment analysis model that would help get an idea about the views of the people in regard to the COVID19 vaccines. Fig-6 describes the workflow followed. Firstly, the data is collected from Kaggle; it is then preprocessed and labeled using Textblob. The model is then trained on the labeled dataset.

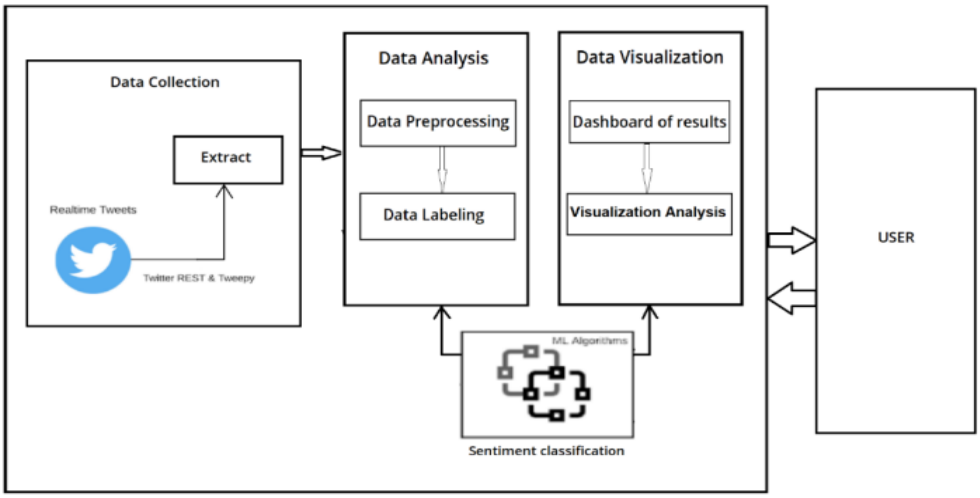

Fig. 6. Workflow of Sentiment Analysis of Tweets

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We then extract our tweet data using the Twitter API, and this new data is classified using our trained ML model. The analysis of tweets has been implemented in 'Python', and visualizations have been done using 'Plotly', 'Seaborn' and 'Matplotlib'. The visualized data is represented in the form of word clouds, hashtags and a sentiment period graph.

B. Dataset for Model Training

We fetched the dataset called "All COVID-19 Vaccines Tweets" from Kaggle. This dataset itself is collected using the tweepy package that accesses the Twitter API. This dataset is updated daily with new tweets regarding COVID-19 vaccines. Main vaccines focused on are Pfizer/BioNTech, Sinopharm, Sinovac, Moderna, Covaxin, Sputnik V and Oxford/AstraZeneca. Once imported, we move onto data-preprocessing.

C. Data Preprocessing

We use the tweet-preprocessor package to perform preprocessing efficiently and helps reduce the complexity of data under analysis. The preprocessing stage consists of a variety of steps:

1. All uppercase letters can be converted to lowercase.
2. Tokenization is the process of removing the hashtags, numbers, URL's and targets (@). Hashtags were removed from the tweet text, but a separate column was created to store them. NLTK Module was used to tokenize all tweets.
3. Stemming has also been performed using PorterStemmer. This helps reduce words to their root form. Words that are not in English are removed. We are primarily interested in English tweets, so non-English words have been removed.
4. Emoticon substitutes- Since emoticons are important in deciding emotion, their polarity is replaced by looking up the emoticon dictionary.
5. Removal of stop words - Stop words have a negative impact on emotion recognition, so they must be eliminated. Both positive and negative tweets have them. Stop words are produced and then overlooked.

D. Feature Extraction

We extract aspects from the preprocessed Twitter dataset using the attribute extraction tool. It is necessary to convert a tweet into a vector that can represent it [14]. We use the TfIDK Vectorizer, which is a method to transforms text to feature vectors that can be used to determine the importance of a word in a collection or corpus.

1. Features are divided into three categories: unigram, bigram, and n-gram features.
2. Speech Elements adjectives, adverbs, verbs, and nouns, for example, are strong examples of subjectivity and emotion.
3. Negation is an important but difficult to interpret feature. The inclusion of a negation normally shifts the sentiment's polarity.

E. Sentiment Analysis

To calculate the sentiment of each tweet, we make use of Textblob. Textblob is a python library that uses the Natural Language ToolKit for sentiment analysis. Textblob returns two properties of a sentence:

1) *Polarity*- range of value lies in the range [-1.0, 1.0], of which -1 is for negative sentiment and 1 for positive sentiment.
2) *Subjectivity* - refers to a person's opinion, judgment or emotion. Its range is between [0, 1.0].

We classify the text as negative, neutral or positive and add a new column to the data frame labeling the tweets sentiment.

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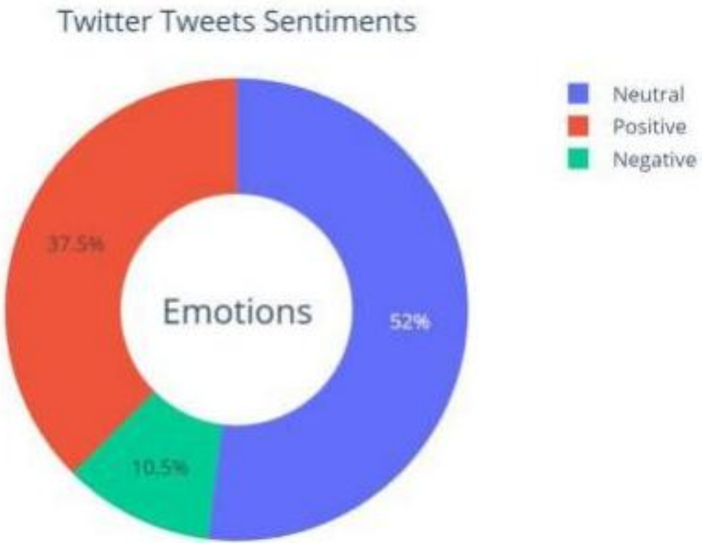

Fig. 7. Sentiment distribution of tweets

F. Building Predictive Model

After completing preprocessing, cleaning and analyzing the sentiment of the tweets, we built our Machine Learning model. We then employ vectorization to convert the text data into numerical features.

Model Selection: We use the Random Forest, Naive Bayes, Decision Tree Classifier. Naïves Bayes Classifier: The Bayes' Theorem assumes mathematical independence of features; thus, a supervised machine-learning technique that uses it is called a Naive Bayes Classifier. Conditional probability is the foundation of the Bayes Theorem. The following equation reflects Bayes' Theorem in probability terms.

$$P(U|V) = \frac{P(V|U)\ P(U)}{P(V)}$$

"P" = probability.

P(U | V) = Chance that event U will occur provided that event V has already occurred.

P(V | U) = Chance that event V will occur provided that event U has already occurred.

P(U) = Probability that event U will occur.

P(V) = Probability that event V will occur.

Random Forest is a multi-decision tree ensemble solution that employs the Bootstrap and Aggregation method, also known as bagging, to perform regression and classification tasks. The basic principle is to merge various decision trees to decide the final output rather than individual decision trees.

Model Evaluation: We use accuracy for model evaluation. i.e., the number of accurate predictions divided by the overall number of predictions.

To build and train our model to predict the sentiment on new tweets, we use Natural Language Processing.

We split the data into 75% training and 25% validation. The target is set to be a One-Hot Encoded as ['Negative', 'Neutral', 'Positive']. Padding and Tokenization are done for each sentence using a tokenizer from TensorFlow Keras Preprocessing.

All the metrics observed during model training are displayed on one plot:

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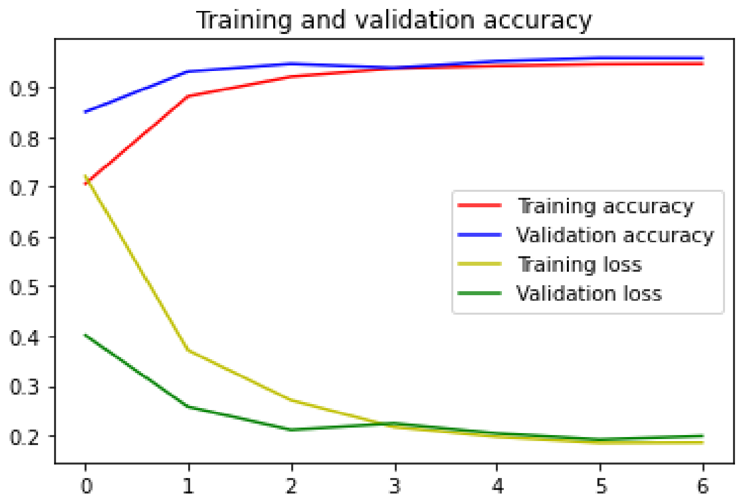


Fig. 8. Model Evaluation

G. Prediction

To obtain Twitter data, we use the Twitter REST API. REST stands for "Representational State Transfer". A package called tweepy is used to access the Twitter API. There are two types of API:

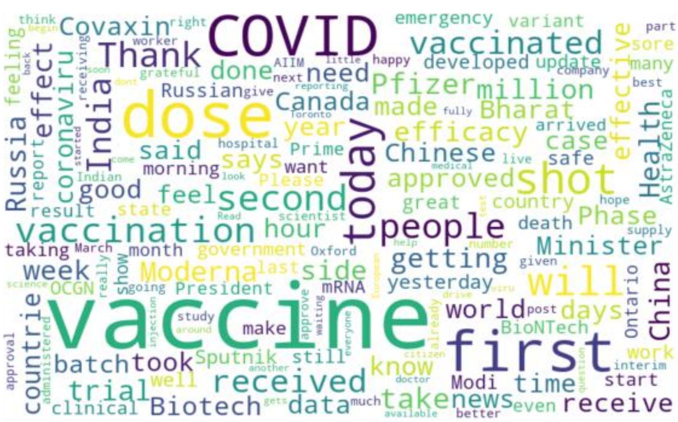
a. Search API: Used to collect data based on hashtags.
b. Stream API: Used to get real-time data.

After collecting data from Twitter, we move on to python-based preprocessing. We run the extraction script for each day of the latest 7-day date range. Since the Twitter API only allows extraction of tweets for a window of 7 days. The following attributes were retrieved from tweets: username, location, tweet text, hashtags, and tweet date. We then once again perform the same preprocessing on this data. On completion, we pass the data from the data frame into the model to predict the sentiment of the new tweets.

H. Tweet Analysis Results

1. Word Cloud

A word cloud is used to represent the words in terms of their frequency in the tweets. The size of words indicates their importance and frequency. Fig 9. Describes the word cloud generated using tweets. Fig-9a was created using all the tweets present, Fig. 9b consists of words from tweets whose sentiment is positive, Fig. 9c word cloud consists of prominent words from tweets whose sentiment is labeled negative, and word cloud in Fig-9d consists of words from tweets having neutral sentiment.



(a)

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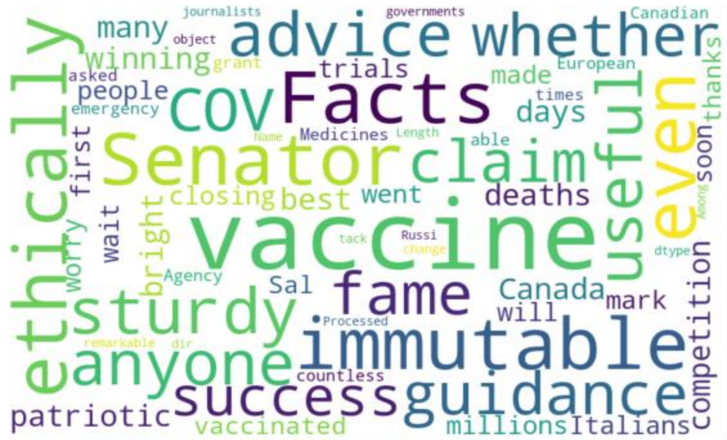

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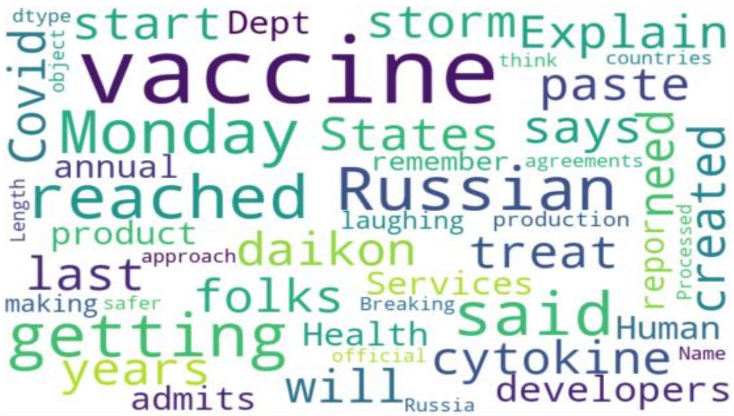

(d)

Fig. 9. Word cloud visualization of (a) All tweets, (b) Positive Tweets, (c) Negative Tweets, (d) Neutral

2. Hashtags

The analysis on hashtags shows the count of the top 10 hashtags used by the people in regards to COVID-19 vaccines. Among the findings in Fig.10, it is seen that most hashtags correspond to the respective COVID-19 vaccine names. Hashtags for Moderna have been used the most, followed by Covaxin. Sinovac and Sinopharm

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by China have the least hashtags. PfizerBioNTech and Sputnik V have almost the same number of counts.

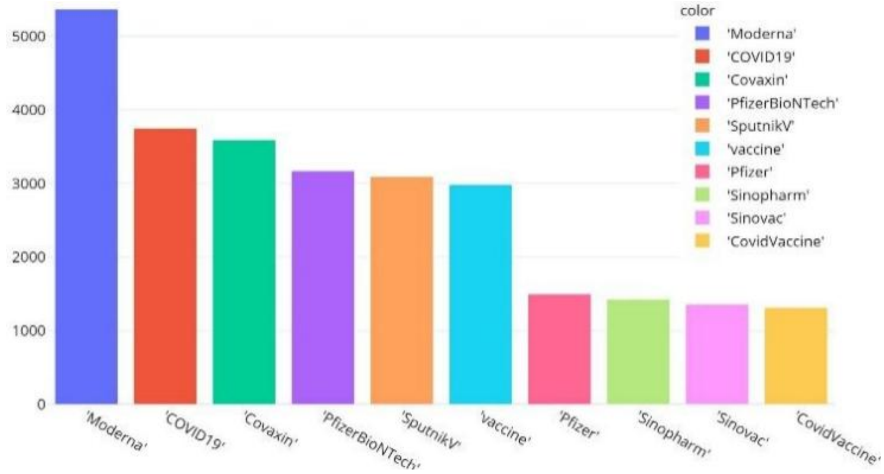

Fig. 10. Top 10 Covid19 Vaccine Hashtags

3. Sentiment Period Graph

The analysis on sentiment from December 20th, 2020 to March 21st, 2021 shows a trend that we find spikes at different dates. Example: The huge spike in tweets on March 1st, 2021, was mainly due to Shri Narendra Modi, India's PM, taking his first shot of the COVID-19 vaccine, thus marking the start of the second phase of vaccination in India.

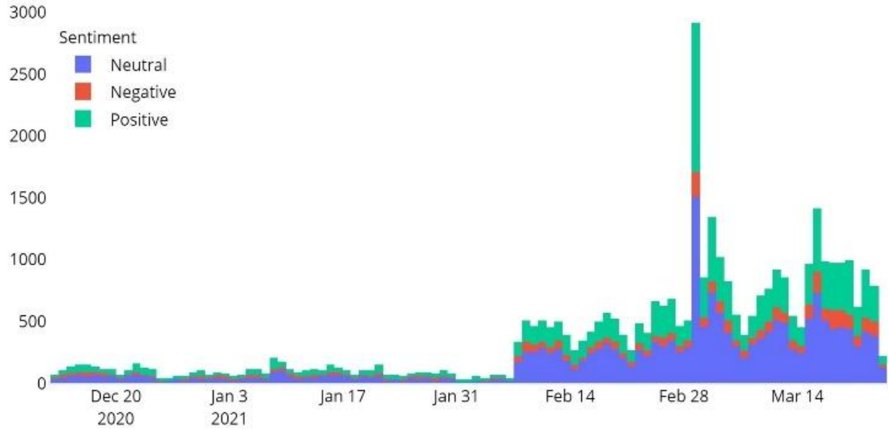

Fig. 11. Histogram showing the trends in tweets

Conclusion

COVID-19 has spread so quickly that it has disrupted the whole globe's tempo. This paper has presented a comprehensive analysis of COVID-19 spread around the world based on the data gathered. The US remains the most affected country by the pandemic. Despite being the virus's epicenter, China had a relatively low number of cases. The impact it has had on sectors that include the economy and education. It reveals the shortcomings of the educational institutions, such as not adopting any online teaching platform or services when the pandemic was in its early stages, resulting in a lot of chaos. It was found that most people had a neutral outlook towards the COVID-19 vaccination phase, and only about 10.5% of tweets were negative.

Future Work

In the future, this paperwork could be expanded to a higher degree. We plan to provide a reliable and effective machine learning approach as a predictive model that uses the latest dataset to anticipate potential cases. We also plan to incorporate sentiment analysis on COVID-19 data from the onset of the virus, which would help us understand the people's mindset and viewpoint during this pandemic phase. One of the key focuses of our future work would be real-time live forecasting. All the above components can be combined into an interactive and user-friendly web-based application.

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