Online Guard: Identifying the misinformation in social media and its impact on COVID-19 vaccination progress in different countries

Sanjida Akter Sharna
Department of computer science
Tennessee Tech University
Cookeville, Tennessee, USA
sasharna42@tntech.edu

William Eberle
Department of Computer Science
Tennessee Tech University
Cookeville, Tennessee, USA
weberle@tntech.edu

Abstract— **The emergence of the novel coronavirus pandemic has caused a myriad of problems worldwide. One such problem is misinformation, which in itself should be considered a risk. Our society and the general public are focused on an extraordinary measure of truth, embellishment and semi-truth that is detrimental to national prosperity, autonomy, health, well-being and public safety. Since the outbreak of the COVID-19 pandemic, popular social media platforms are flooded by exaggerated phony news which is affecting our society. Many of the online falsehoods don't have apparent sources or intentions, rather, some niche groups often start mobilizing to endorse their agendas through the rumors. Although the pertinent tools and existing techniques can support fact-checking and identification of conspiracy, misinformation, and negative sentiment at various stages, a complete end-to-end solution is complicated. In this paper, we propose a thorough analysis and identification system named Online Guard using natural language processing tools and supervised learning techniques to identify the relationship between misinformation from the negative sentiment of COVID-19 vaccine-related tweets and vaccination progress rate and its impact in different countries. For this purpose, we will use a COVID-19 *all vaccines tweet* dataset to identify and analyze misinformation, and another dataset named country vaccination that shows vaccine rollout and vaccination progress in different countries. The aim of this project is to identify the relationship between spreading misinformation, negative emotions on Twitter, and its impact on vaccination progress for a particular time period.**

Keywords—COVID-19, vaccine, twitter, social media, misinformation

I. INTRODUCTION

The rise of social media has unleashed an unprecedented and false spread of information in our society. This becomes even more apparent during a crisis like the COVID-19 pandemic. The emergence of various forms of malicious content, commonly known as fake news, and the many dangers of social media platforms that users may encounter in the online ecosystem are also unrecognized. The destructive nature of fake news information leads to duplication with other concepts that arise from forged information that tends to mimic news content. In fact, fake news can take many forms. Therefore, it is necessary to distinguish between "misinformation" and "disinformation". The former makes a claim that the information is incorrect or inaccurate, and the latter explains the incorrect information that was deliberately disseminated to mislead people. The outbreak of coronavirus disease (COVID-19) has caused great concern among people. Since December 2019, it has had a great influence on the opinions of the general public and society. In addition to the disease itself, the pressure from the pandemic and the fear of its spread, it's a psychological burden. The coronavirus pandemic has given a great boost to social media on this topic. The abuse of the COVID19 crisis took root in critical moments of uncertainty and fear, leading to an overwhelming amount of misinformation about the problem. Therefore, it is also necessary to identify the misinformation about virus-related topics. From distinguishing misinformation and negative emotions of tweets, we can get insight about people's impression toward vaccine.

There has been a concerted worldwide exertion to create and test COVID-19 vaccine since the pandemic was announced. It is estimated that at least over 70% of the population will need to be vaccinated [1], [2] to reach some level of herd immunity. While classic research helps to explore public health perspectives [3] it is increasingly used by social media to discuss and exchange perspectives on health issues associated with the development of a COVID-19 vaccine. In fact, users of social media are exposed to negative emotions and false information that can affect an individual's view and lead to hesitation or refusal to get vaccinated [4]. Thus, the following research question should be addressed

RQ1: Why identifying misinformation and negative emotions are important to provide an intimation of terrors lurking inside social media platforms (Twitter) during the pandemic crisis?

RQ2: How propagation and acceptance of covid vaccine activities are intertwined with social media platforms' increasing misinformation?

In this proposed approach, we are developing a tool using natural language processing and machine learning techniques that will perform sentiment analysis and time series analysis of the COVID-19 vaccination dataset for misinformation and negative emotions for a particular time period. we will perform a time series analysis to analyze the progress of vaccination in a similar time period. we will perform a quantitative analysis on the trend of negative emotion and vaccination progress and identify their correlation for certain communities, to see how different communities are affected by misinformation from social media(twitter).

The paper is organized as followed. First, we are doing a background study about the importance of identifying misinformation, fake news, negative sentiment and impact of these on vaccine rollout among people. Second, we are proposing an online guard which is misinformation and negative emotion detection tool for the COVID-19 tweet dataset. Third, we will analyze how misinformation is affecting the vaccine acceptance rate and spreading in a particular time period.

II. Related Work

A. *Journalistic Fact-Checking of Information in Pandemic: Stakeholders, Hoaxes, and Strategies to Fight Disinformation during the COVID-19 Crisis in Spain*[5]

Prior research has extensively studied the spread of misinformation related to COVID-19. Researchers have discussed fact-checking the current status and society's information needs and Journalism content which are using complex techniques such as content analysis of refuted information of major Spanish fact-checking platforms and queries about these stakeholders[5]. The results confirm the quantitative and qualitative evolution of disinformation. The phenomenon of misinformation in uncertain situations like COVID-19 pandemic, proliferate and expand. This leads to a more noteworthy caution within the circulation of disinformation and to a more noteworthy level of trouble when it comes to screening and administration.

B. *Covid-19 on social media: analyzing misinformation in twitter conversations* [6]

In this paper, the authors demonstrated that more people rely on social media platforms news, for identification of misinformation and disclosure of the nature of COVID-19-related online discourse [6]. To do this, they collected streaming data related to COVID-19 from March 1, 2020, have identified untrusted and misleading content based on the Twitter API. They have verified the source and investigated the narrative circulation in the disinformed tweets and distribution of interactions with these tweets. In addition, they provide an example of distribution pattern for famous misinformative tweets. An updated analytics suite of accessible tools is also published by authors to track the nature of online discourse and disinformation about COVID-19 tweets from March 1st to June 5th, 2020. The dashboard displays a daily list of identified misinformation which includes topics, moods, new trends, and more of Twitter's COVID-19 discourse.

C. *Sentiment Analysis of COVID-19 tweets by Deep Learning Classifiers—A study to show how popularity is affecting accuracy in social media* [7]

In this third paper authors have extensive research of sentiment analysis by deep learning classifier [7]. This study demonstrates that though human beings have tweeted frequently positive tweets concerning COVID-19, but netizens have been busy engrossed in re-tweeting the negative tweets and said that no beneficial phrases will be located in Word Cloud or computations using word frequency in tweets. The claims had been verified via a proposed deep learning classifier with admissible accuracy as much as 81%. Apart from those the authors have proposed the implementation of a Gaussian membership function-based fuzzy rule base to successfully perceive sentiments from tweets. The accuracy for the stated classifier yields 79%. In addition to the above, this article proposes an implementation of fuzzy logic to tame emotional ambiguity. Because fuzzy sets are ideal for resolving day to day life ambiguity, the authors proposed an initial fuzzy logic integration to efficiently handle sentiment identification in tweets.

D. *The relationship between fear of COVID-19 and intention to get vaccinated. The serial mediation roles of existential anxiety and conspiracy beliefs*[8]

This study [reference] was conducted in a crossover design with 223 French adults (female: 69.5%, male: 30.5%, mag = 30.26, SD = 13.24, range: 18-75 years of age) who responded to an online survey [8]. Using a sequential mediation model, the authors tested the effect of fear of COVID-19 on vaccination intentions and the mediating effect of existential anxiety and conspiracy beliefs. They have presented some hypothesis which are "Fear of COVID-19 is positively related to the intention to get vaccinated", "Fear of COVID-19 is positively related to existential anxiety", "Existential anxiety is positively related to conspiracy beliefs", "Conspiracy beliefs are negatively related to intention to get vaccinated".

However, none of the mentioned studies have discussed how the misinformation of social media can have a negative impact on overall vaccination progress around the world. In this work, we will address the research gap.

III. Data

For this project, we have collected two data set from the Kaggle site. One is COVID-19 all vaccines tweet dataset [9] and another is country vaccination dataset [10]. With the first dataset we will analyze and identify misinformation for a time series and with another dataset we will analyze the vaccination propagation in different country. The relationship of misinformation in social media has an impact on vaccine acceptance rate can be analyzed with the help of sentiment analysis from COVID-19 all vaccines tweet dataset and vaccine

Identify applicable funding agency here. If none, delete this text box.

roll out rate analysis in different countries from country vaccination dataset. Both data sets are collected using `tweepy` Python package to access Twitter API.

TABLE I. ATTRIBUTE DESCRIPTION FOR COVID-19 ALL VACCINES TWEET DATASET

Attribute Name	Attribute Descriptions
user_location	The location the twitter user
text	Text content of the tweet
date	Date of the tweet
User verified	The verification of twitter user

COVID-19 all vaccines tweet dataset is in CSV file format and has 16 columns and 228K rows in total [9]. For our analysis, we will be using the user location, text, user verified and date attributes which is described in TABLE 1. We are taking user location to keep track of the region of the user. Then the text column is the most significant column here as we will perform sentimental analysis on this tweet text data. The date column is taken for further time series analysis. The data is collected over the period of December 20, 2020 to 23 November 2021.

TABLE II. ATTRIBUTE DESCRIPTION FOR COUNTRY VACCINATION DATASET

Attribute Name	Attribute Descriptions
country	The country for which the vaccination information is provided
date	Date for the data entry
total_vaccinations	The absolute number of immunizations in the country
people_vaccinated	The number of people who receive at least one vaccine shot
people_fully_vaccinated	The number of people received entire set of vaccine immunization scheme
daily_vaccinations	The number of vaccinations for that date/country
daily_vaccinations_per_million	Ratio (in ppm) between vaccination fully immunized and total population for the date in the country.

The other dataset which is country vaccination is also in CSV file format [10]. This dataset consists of 15 columns and around 39k rows. From this data set we will use country, date, total vaccinations, people vaccinated, people fully vaccinated, daily vaccinations, daily vaccinations per million column attributes and which is collected over around 9 months from December 1, 2020 to August 20, 2021 and the attributes are described in TABLE II. As from this dataset we will analysis vaccine progress rate in different country that's why the country attribute is chosen. The date attribute is necessary for our time series analysis. Other attributes like total vaccinations, daily vaccinations etc were taken to perform the analysis of daily vaccination progress and roll out rate.

we will use the data ranging from January 2021 to September, 2021, for both the datasets.

IV. DATA PREPARATION

For preparing the data to feed the model as input, we have categorized data preparation in few steps which are dropping the unnecessary columns, handling the missing values, formatting the date column into date format and finally data cleaning step. In Figure: 1, we have illustrated the data processing steps for COVID-19 all vaccines tweet dataset and in Figure: 2, we have illustrated the data processing steps for country vaccination dataset.

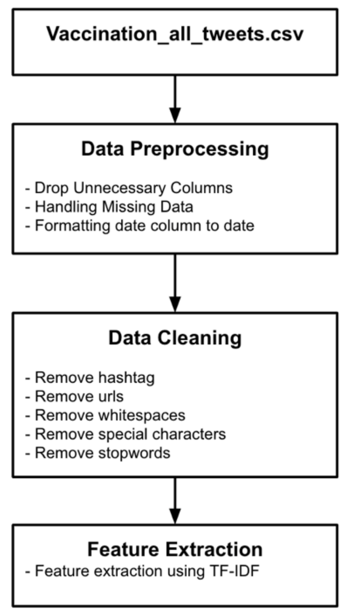

Figure 1: COVID-19 all vaccines tweet dataset data preparation

A. *Data pre-processing*

Initially we have dropped the unnecessary columns from both datasets to reduce the data dimensionality. From COVID-19 all vaccines tweet dataset we have removed the id, user name, user location, user description, user created, user followers, user friends, user favorites, hashtags, source, favorites, is retweet columns as they are irrelevant for sentiment analysis for our scope of project. From country vaccination dataset we have dropped the iso code, daily vaccinations raw, total vaccinations per hundred, people vaccinated per hundred, people fully vaccinated per hundred, vaccines, source name, source website as these columns are not necessary for analysis of daily vaccination progress rate which is the objective of using this dataset for the project. In both datasets, the missing values were auto handled as the missing values were replaced with null and date columns were formatted into date format as date columns will be needed for time series analysis further.

B. *Data cleaning*

For only COVID-19 all vaccines tweet dataset, we need to clea n the data as the text data columns contain unnecessary hashta gs, urls, whitespaces, special characters and stop words which are insignificant for sentiment analysis.

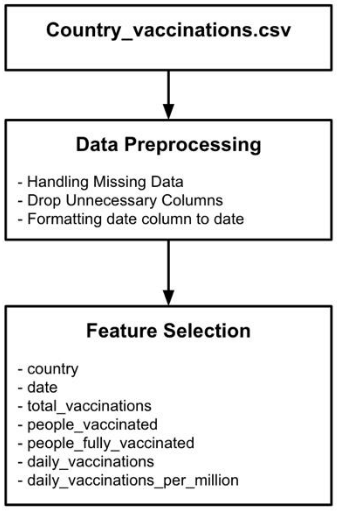

Figure 2: Country vaccination dataset data preparation

C. *Data labeling*

As our preprocessed COVID-19 all vaccines tweet dataset was not labeled for sentiment such as positive, negative or neutral that's why we labeled our data using TextBlob[14] which is a python library for processing textual data for sentiment analysis.

V. Feature Extraction

A. *Text Feature Extraction*

For COVID-19 all vaccines tweet dataset, Term Frequency–Inverse Document Frequency(TF-IDF) is the technique we have used for feature extraction. TF-IDF is a fairly common technique used for text mining. While BoW gives tokens, TF-IDF looks at all tokens and compares their frequencies to find the most important one [11]. To explain TF-IDF more in depth, we can spilt it into its two components: term frequency and inverse document frequency. With term frequency, the score is computed between a token t and a script, based on the weight of t in the script s [12]. The simplest approach is to assign the weight to be equal to the number of occurrences of token t in script s [12]. Figure :3 shows an example of what the calculation should look like for Term Frequency [13].

$$TF(t,s) = \frac{\text{occurences of token } t \text{ in script } s}{\text{total count of tokens in script } s}$$

Figure 3: Term Frequency Calculation

Inverse document frequency is the inverse of document frequency. Document frequency is defined to be the number of scripts in the collection that contain a term t [12]. The inverse comes into play when the total count of scripts in the dataset is divided by the count of scripts in which token t appears at least once. Figure: 4 is a representation of how the Inverse document frequency calculation is done[13].

$$IDF(t) = \log_{10}\left(\frac{\text{total count of scripts in the dataset}}{\text{count of scripts in which token } t \text{ appears at least once}}\right)$$

Figure 4: Inverse document frequency calculation

As described by Manning et al., TF-IDF is the combination of "...the definitions of term frequency and inverse document frequency, to produce a composite weight for each term in each document..." [12]. Figure: 5 shows the calculation of TF-IDF[13].

$$TF-IDF(t,s) = TF(t,s) * IDF(t)$$

Figure 5: TF-IDF calculation

Figure: 6 demonstrates the TF-IDF values as matrix representation for each of the tokens in the source code files for tweet text data.

airport	amazing	amp	...	want	way	weather	wife	wifi	won	work
0.0	0.0	0.000000	...	0.0	0.0	0.0	0.000000	0.0	0.0	0.000000
0.0	0.0	0.000000	...	0.0	0.0	0.0	0.000000	0.0	0.0	0.000000
0.0	0.0	0.282154	...	0.0	0.0	0.0	0.000000	0.0	0.0	0.000000
0.0	0.0	0.457258	...	0.0	0.0	0.0	0.000000	0.0	0.0	0.000000
0.0	0.0	0.000000	...	0.0	0.0	0.0	0.000000	0.0	0.0	0.000000
0.0	0.0	0.330530	...	0.0	0.0	0.0	0.000000	0.0	0.0	0.000000
0.0	0.0	0.000000	...	0.0	0.0	0.0	0.000000	0.0	0.0	0.000000
0.0	0.0	0.000000	...	0.0	0.0	0.0	0.769396	0.0	0.0	0.000000
0.0	0.0	0.497540	...	0.0	0.0	0.0	0.000000	0.0	0.0	0.000000
0.0	0.0	0.000000	...	0.0	0.0	0.0	0.000000	0.0	0.0	0.000000
0.0	0.0	0.000000	...	0.0	0.0	0.0	0.000000	0.0	0.0	0.000000
0.0	0.0	0.000000	...	0.0	0.0	0.0	0.000000	0.0	0.0	0.000000

Figure 6: TF-IDF matrix representation

B. *Feature Selection*

For country vaccination dataset we have selected the features manually. For the scope of our project, we have selected country, date, total vaccinations, people vaccinated, people fully vaccinated, daily vaccinations, daily vaccinations per million as most significant feature to be used for exploratory analysis. We have taken the country feature as we will analyze vaccination progress in different country. Then we have taken the date feature to perform time series analysis. Other features like people fully vaccinated, daily vaccinations etc were taken under consideration to analysis the vaccine roll out rate on daily basis.

VI. EXPERIMENTAL SETUP

In this experiment, we have use python and python packages such as numpy pandas for data processing, scikit-learn for applied machine learning algorithm, neattext and nltk for raw tweet text data processing. We run all the experiment on a machine with 8 GB RAM and core i3 processor running the windows 10 operating system using jupyter notebook.

Using the above-described system configuration, initially we preprocessed the COVID-19 all vaccines tweet and country vaccination dataset such as handling missing data, removing unnecessary columns, and formatting date format. After that, we cleaned the raw tweet text data from COVID-19 all vaccines tweet dataset such as removing hashtags, URLs, whitespaces, special characters, stop words. Details will be found in Figure 1. For country vaccination data set again we have preprocessed the data such as dropping the unnecessary columns. Then we used manual feature selection technique for selecting important features. For labeling the tweet text data on the basis of their sentiment we have used Textblob python library [14] which returns a named tuple of the form sentiment (polarity, subjectivity). The polarity score and subjectivity is usually a float value range withing [-1.0, 1.0]. After the feature extraction, using TFIDF vectorizer and get_feature_names() function we will train our model using logistic regression and naïve bayes algorithm for sentiment analysis. We are using Naïve bayes [15] and logistic regression as it works well with text data classification and it can learn parameter using a small amount of training dataset. We will then split our dataset into train and test sets where the training data set to 70% and the test data set to 30%. We also set the random state attribute so our results could be reproduced.

For country vaccination dataset, we have handled the missing values and unnecessary columns were dropped and then significant features were selected for vaccination roll out analysis. We will perform time series analysis on daily vaccination record for different country which is an exploratory analysis technique. After this step, we will validate our hypothesis whether daily negative tweets from COVID-19 all vaccines tweet dataset has a negative correlation with vaccination progress. The below figure 7 is showing the flow diagram of our experimental setup.

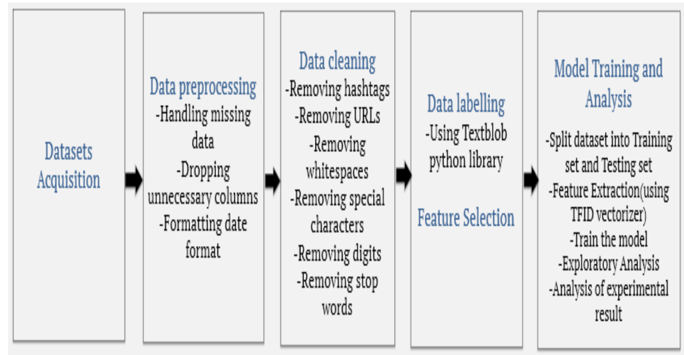

Figure 7: Flow Diagram of Experimental Setup

VII. EXPERIMENTAL RESULT AND ANALYSIS

A. *Evaluation Metrics*

An evaluation metric quantifies the performance of a predictive model. This typically involves training a model on a dataset, using the model to make predictions on a holdout dataset not used during training, then comparing the predictions to the expected values in the holdout dataset. For classification problems, metrics involve comparing the expected class label to the predicted class label or interpreting the predicted probabilities for the class labels for the problem [16]. There are standard metrics that are widely used for evaluating classification predictive models, such as classification accuracy, classification error, precision, recall, F measure, and PR-AUC etc. The confusion matrix provides more insight into not only the performance of a predictive model but also which classes are being predicted correctly, which incorrectly, and what type of errors are being made. In this type of confusion matrix, each cell in the table has a specific and well-understood name, summarized as follows [17].

- **True Positive (TP):** The predicted value matches the actual value. The actual value was positive and the model predicted a positive value.

- **True Negative (TN):** The predicted value matches the actual value. The actual value was negative and the model predicted a negative value.

- **False Positive (FP) – Type 1 error:** The predicted value was falsely predicted. The actual value was negative but the model predicted a positive value.

- **False Negative (FN) – Type 2 error:** The predicted value was falsely predicted. The actual value was positive but the model predicted a negative value.

Confusion matrix gives us a holistic view of how well our classification model is performing and what kinds of errors it is making. Various evaluation metrices are presented in the below TABLE III.

TABLE III. DESCRIPTION OF EVALUATION METRICES

Metric	Equation	Explanation
Accuracy (acc)	$\frac{TP+TN}{TP+TN+FP+FN}$	The fraction of observations that are corr classified.
Precision (P)	$\frac{TP}{TP+FP}$	The fraction of correctly classified pos classes from the set of observations that predicted to be positive.
Recall (R)	$\frac{TP}{TP+TN}$	The fraction of correctly classified pos classes from the set of observations that classified correctly.
F measure	$\frac{2*P*R}{P+R}$	The harmonic mean of precision and recall rics.

Precision summarizes the fraction of examples assigned the positive class that belong to the positive class. Recall summarizes how well the positive class was predicted and is the same calculation as sensitivity. Precision and recall can be combined into a single score that seeks to balance both concerns, called the F-score or the F-measure.

B. Result and Analysis

As our preprocessed COVID-19 all vaccines tweet dataset was not labelled according to sentiment, we used TextBlob's senti ment detector to understand the tweet's sentiment, whether pos itive, negative, or neutral, since misinformation is often associ ated with negative sentiment of tweets. A tweet's overall subje ctivity was also provided through TextBlob's analysis. We got 137494 Neutral sentiment, 68318 Positive sentiment and 2239 5 Negative sentiment from TextBlob analysis.
It is also necessary to check whether the user is verified or no, how many followers the account has, to understand how a new s source cited or retweeted in a tweet. All these factor affects r eliability of any tweet. By cross-referencing the cited news so urce with a list of already-verified resources, and cross-checki ng all the mentioned factor, it is possible to reinforce if a Twe et is misinformative or not. This analysis evaluates our RQ1. F igure: 8 shows the percentage analysis of positive, negative an d neutral tweets.

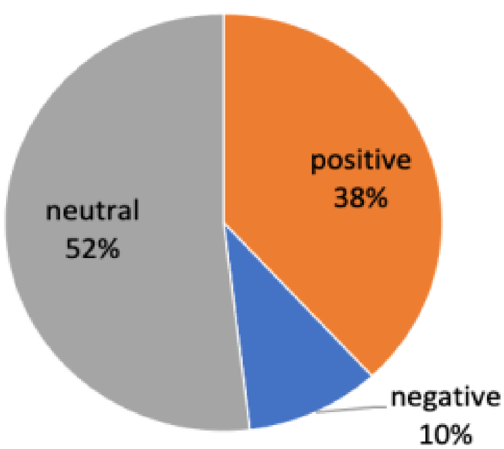

Figure 8: TextBlob Sentiment Analysis

Now taking the Textblob's sentiment analysis as ground truth, the resultant sentiment analysis information was used to feed the models as input. After using TFIDF vectorizer for feature extraction, Logistic Regression model and Naïve Bayes model with 5-fold cross validation were used for classification. TABLE IV shows the results of the performance evaluation of the proposed models in terms of various performance evaluation metrics.

TABLE IV. DESCRIPTION OF PERFORMANCE EVALUATION

Model	Sentiment	Precision	Recall	F1-Score	Accuracy
Logistic Regression	Negative	0.87	0.33	0.48	0.80
	Neutral	0.77	0.98	0.87	
	Positive	0.90	0.61	0.73	

Model	Sentiment	Precision	Recall	F1-Score	Accuracy
Naïve Bayes	Negative	0.78	0.27	0.40	0.77
	Neutral	0.78	0.93	0.85	
	Positive	0.75	0.62	0.68	

In TABLE IV we can see that the accuracy of Naïve Bayes model is 77.21% and the accuracy of Logistic Regression model is 80.44%. Performance of both models are relatively close which is an indication that our tweet-text-data sentiment classification was on track. However, the Logistic Regression model showed relatively better performance than Naïve bayes in term of accuracy. According to polarity and subjectivity (from Textblob's analysis), negative sentimental tweets are more likely to be misinformative and contains higher likelihood of being against precaution. Additional details like verified user, user follower, retweets etc were surmised through python programming, and a misinformation filtering function was developed to automate the process of filtering misinformation from negative sentiment further.

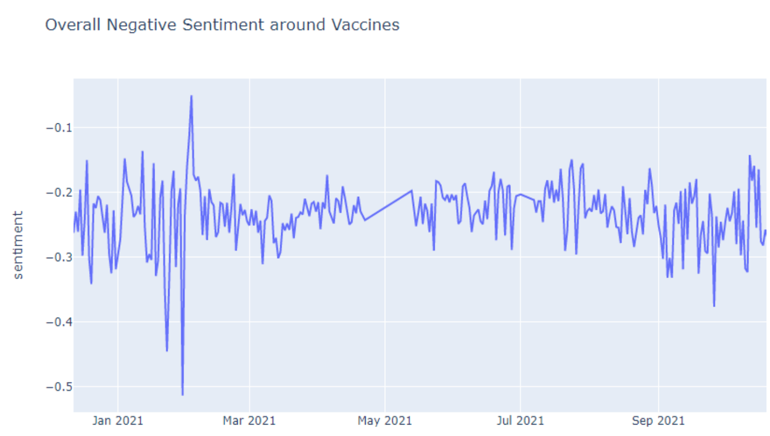

Figure 9: Time Series Analysis of Overall Negative Sentiment

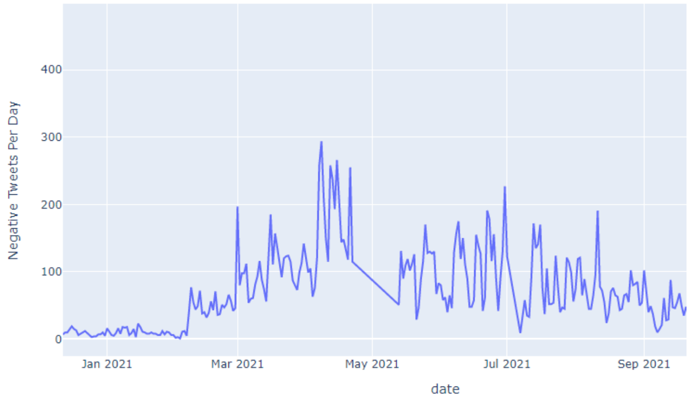

Figure 10: Time Series Analysis of Negative Tweets per day

Later we have performed time series analysis on negative sentimental tweets to analysis overall negative sentiment around vaccines which is shown in Figure 9. From Figure 9, we can see that throughout the time period (January 2021- September 2021) the sentiment values tend to be more negative and closer to sentiment subjectivity -0.05 which is an indication of misinformation. Another time series analysis was performed to visualize the negative tweets per day which is shown in Figure 10. In this Figure 10, we can observe that throughout the time period (January 2021- September 2021) the number of per day negative tweets is huge and on April 26th 2021, it was 299.

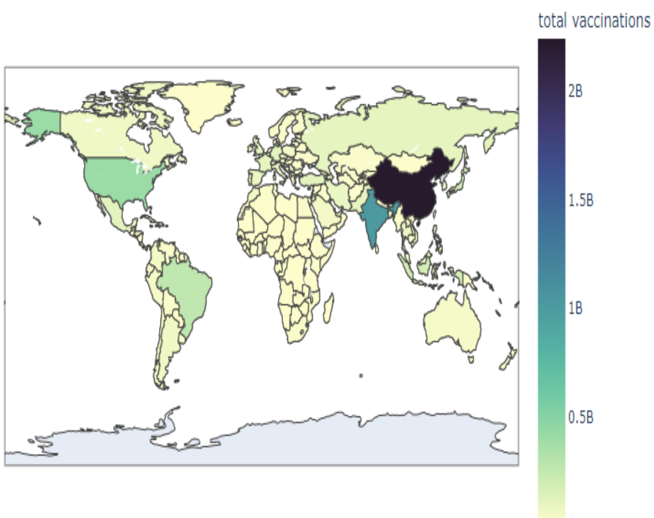

Figure 11: Total vaccination in different countries (January 2021- September 2021)

From the country vaccination dataset, we performed various exploratory analysis over the same time period (January 2021- September 2021) to visualize the impact of misinformation and negative sentiment in different countries which evaluate our RQ2.

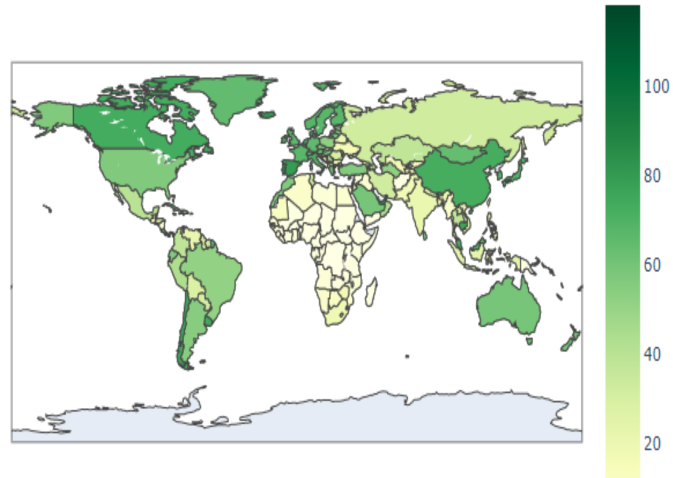

Figure 12: Fully vaccinated percentage in different countries (January 2021- September 2021)

From the figure 11, we can see that in most of the countries total vaccination progress is below .5 billion. From figure 12, we can also visualize that the fully vaccinated percentage in most of the countries over the same time period (January 2021- September 2021) is below 50%.

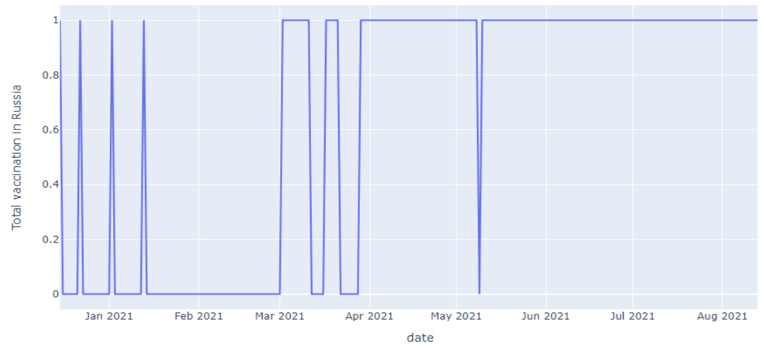

Figure 13: Time Series Analysis of Total vaccination in Russia (January 2021- September 2021)

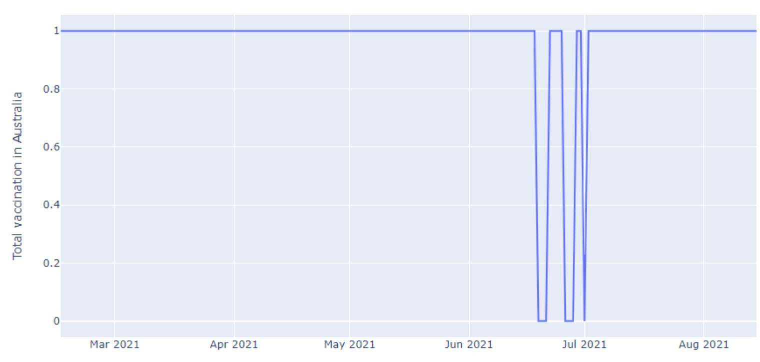

Figure 14: Time Series Analysis of Total vaccination in Australia (January 2021- September 2021)

We have also performed time series analysis on different countries to reinforce our hypothesis that misinformation and negative sentiment on twitter has direct or indirect impact on vaccination progress and acceptance rate. From figure 13 and Figure 14 we can observe that in Russia and Australia total vaccination progress (from January 2021- September 2021) is very low and withing particular time range the curve downgraded several times.

C. Threats to Validity

During our experiment and observation, we have found the below threats to validity.

In our experiment, filtering of misinformation from negative sentimental tweets are performed developing a function using python programming language. For large dataset this method could perform poorly and the result could be biased. So, this could be a threat to validity for our existing system. However, for our scope of experiment and dataset this technique performs well.

VIII. CONCLUSION AND FUTURE WORK

In this paper, we proposed Online Guard which is an identification system of misinformation and negative sentiment from tweet data using Natural language processing and supervised techniques. We have also performed time series analysis and exploratory analysis on our dataset to visualize and observe the impact misinformation on twitter and its impact on different country. Both of our models perform closely in term of accuracy; however, Logistic Regression model provide better accuracy. Our analysis showed that identifying misinformation and negative emotions are significant to provide an insight that misinformation and negative sentiment have higher likelihood of being against safeguard and vaccines lurking inside social media platforms (Twitter) during the pandemic crisis. Overall, this paper showed and discussed the effectiveness of our proposed misinformation identification system and analysis of the propagation and acceptance of COVID-19 vaccine activities are more likely to be negatively co-related (hypothesis) with social media platforms' increasing misinformation. Focus of our future work will be to incorporate more efficient way of distinguishing and filtering misinformation from negative sentiment using Excel macro. We will also focus on cross referencing different news sources, references to boost our sentiment analysis process. Right now, we have used static datasets for this analysis, in future we can use largescale dataset and directly extracted data set from Twitter using Twitter API. For our scope of experiment, we have just used text data, in future we can analysis image data to enhance our sentiment analysis tool.

ACKNOWLEDGEMENT

I would like to thank Dr. William Eberle for his support and guidance in conducting the experiment and navigating the process of writing this paper.

REFERENCES

[1] Scrima, Fabrizio, Silvana Miceli, Barbara Caci, and Maurizio Cardaci. "The relationship between fear of COVID-19 and intention to get vaccinated. The serial mediation roles of existential anxiety and conspiracy beliefs." *Personality and Individual Differences* 184 (2022): 111188.

[2] Micallef, Nicholas, Bing He, Srijan Kumar, Mustaque Ahamad, and Nasir Memon. "The role of the crowd in countering misinformation: A case study of the COVID-19 infodemic." In *2020 IEEE International Conference on Big Data (Big Data)*, pp. 748-757. IEEE, 2020.

[3] Peretti-Watel, Patrick, Valérie Seror, Sébastien Cortaredona, Odile Launay, Jocelyn Raude, Pierrea Verger, Lisa Fressard et al. "A future vaccination campaign against COVID-19 at risk of vaccine hesitancy and politicisation." *The Lancet Infectious Diseases* 20, no. 7 (2020): 769-770

[4] Yousefinaghani, Samira, Rozita Dara, Samira Mubareka, Andrew Papadopoulos, and Shayan Sharif. "An analysis of COVID-19 vaccine sentiments and opinions on Twitter." *International Journal of Infectious Diseases* 108 (2021): 256-262.

[5] López-García, Xosé, Carmen Costa-Sánchez, and Ángel Vizoso. "Journalistic fact-checking of information in a pandemic: Stakeholders, hoaxes, and strategies to fight disinformation during the COVID-19 crisis in Spain." *International Journal of Environmental Research and Public Health* 18, no. 3 (2021): 1227.

[6] Sharma, Karishma, Sungyong Seo, Chuizheng Meng, Sirisha Rambhatla, and Yan Liu. "Covid-19 on social media: Analyzing misinformation in Twitter conversations." *arXiv preprint arXiv:2003.12309* (2020).

[7] Chakraborty, Koyel, Surbhi Bhatia, Siddhartha Bhattacharyya, Jan Platos, Rajib Bag, and Aboul Ella Hassanien. "Sentiment Analysis of COVID-19 tweets by Deep Learning Classifiers—A study to show how popularity is affecting accuracy in social media." *Applied Soft Computing* 97 (2020): 106754.

[8] Scrima, Fabrizio, Silvana Miceli, Barbara Caci, and Maurizio Cardaci. "The relationship between fear of COVID-19 and intention to get vaccinated. The serial mediation roles of existential anxiety and conspiracy beliefs." *Personality and Individual Differences* 184 (2022): 111188.

[9] https://www.kaggle.com/gpreda/all-covid19-vaccines-tweets

[10] https://www.kaggle.com/gpreda/covid-world-vaccination-progress

[11] A. Rahman and L. Williams, "Characterizing Defective Configuration Scripts Used for Continuous Deployment," IEEE Xplore Digital Library, 28- May-2018. [Online]. Available: https://ieeexploreieee-org.ezproxy.tntech.edu/document/8367034. [Accessed: 19-Apr-2020].

[12] C. D. Manning, P. Raghavan, and H. Schutze, Introduction to Information Retrieval. New York, NY, USA: Cambridge University Press, 2008.

[13] Joachims, Thorsten. A Probabilistic Analysis of the Rocchio Algorithm with TFIDF for Text Categorization. Carnegie-mellon univ pittsburgh pa dept of computer science, 1996.

[14] https://textblob.readthedocs.io/en/dev/quickstart.html?fbclid=IwAR0qWD8xzKac7LKD_U2hP7njTRZWxIRQGyL6YWhHOjtsJBhdTgc6DCxzn0s

[15] Murphy, Kevin P. "Naive bayes classifiers." University of British Columbia 18, no. 60 (2006): 1-8.

[16] https://machinelearningmastery.com/tour-of-evaluation-metrics-for-imbalanced-classification/#:~:text=An%20evaluation%20metric%20quantifies%20the,values%20in%20the%20holdout%20dataset.

[17] https://www.analyticsvidhya.com/blog/2020/04/confusion-matrix-machine-learning/#:~:text=A%20Confusion%20matrix%20is%20an,by%20the%20machine%20learning%20model.

IEEE conference templates contain guidance text for composing and formatting conference papers. Please ensure that all template text is removed from your conference paper prior to submission to the conference. Failure to remove template text from your paper may result in your paper not being published.