International Journal of Research in Computer & Information Technology (IJRCIT),
Vol.7, Issue 3, June 2022
E-ISSN: 2455-3743
Available online at www.ijrcit.co.in

Social Media Sentiment Analysis for Covid-19 Tweets Based on Machine Learning

[1]Swati Ganeshrao Dhoke, [2]Dr. S. R. Gupta, [3]Prof. R. A. Kale

Abstract— In a time of crisis, social media tends to be people's go-to place for sharing information quickly and catering to a wider audience. This generates a significant amount of data, some of which are extremely valuable to be used for relief work. Here, we intend to study the nature of social-media content generated during the ongoing corona epidemic. We evaluate our techniques on a Twitter dataset through a set of carefully designed experiments, to see which method fits best to extract useful information for this particular type of data.

Keywords— Sentiment Analysis, Corona Epidemic, Coronavirus, Machine Learning, Social-Media

I. Introduction

Coronavirus, a unique virus took the world by surprise with the first case noted in November 2019 in Wuhan, China, and successfully spread to all nations of the world. Since its inception, the virus created a pandemic which has been a major conversation on almost all microblogging sites. The negative effect of this virus on every aspect of human existence was enormous and it became a major issue in the social interaction of human beings due to its airborne nature. The virus has claimed millions of lives in different countries, the United States of America tops the chart with 621293 deaths as of the 4th of July 2021, with Brazil taking second place with 524,417 deaths with an increase in death of 718. India makes the third place with 402,757 deaths with increasing daily deaths of 742 [1]. The total number of confirmed cases worldwide as of this date is 184,498,556 with the total recovered being 168,785.185. The total number of deaths recorded is about 3,991,905. These numbers throw the world into chaos as humans have never seen or experienced a virus like this. There were a lot of isolation, school closure, job losses, illness, mental breakdown, loss of income, and depression. There was a complete shutdown with no movement of some nations to understand the nature of this virus and be able to provide an adequate solution to eliminate or minimize the spread. There were a lot of restrictions put in place restricting people from traveling and connecting whether for business, networking, or to meet with loved ones. Although the increase in confirmed cases and deaths is no longer at its peak, its effect on human life and activities has taken a drastic turn. Social distancing has been inculcated into daily activities, unemployment increased drastically, school closure is still very paramount in most nations, and the economy of most nations is suffering. All these have in more ways than one, had adverse effects on human beings' mental health. Humans are social beings and therefore the effect of this virus has led to loneliness, depression, and an increase in mental health cases. A recent survey carried out by Census Bureau and the Centers for Disease Control and Prevention shows that coronavirus is associated with rapid rises in psychological distress across many nations most especially among women, the less educated, and some minority ethnic groups like black Americans [2]. The fear of the virus has also triggered new mental illnesses which means that the measurable impact is greater than the actual number of casualties. Between April 2020 and March 2021, the google trend on Covid and its relationship with mental health shows how consistent the trend is and how worried people are. From the trend, the top five countries are North American countries, South Africa, Ireland, and some parts of Pakistan.

With this virus, there has been an increase in mental health issues. The various problems that came along with the virus, such as job loss, isolation, depression, loss of income, homeschooling, and a lot more have had quite a lot of mental stress and this illness has increased drastically. The government does carry out surveys from time to time to understand people's perception of the virus as it relates to mental health but this method is tedious, time-consuming, and expensive. Even with the survey, only a minute percentage of the population can be reached and this sample is too small to predict and help health care practitioners make proper diagnoses and create solutions for the eradication of this pandemic. With Twitter data, there is access to free large data. Although Twitter data is not reliable as there may be false tweets, false tweets can be detected and government can rely on this data from initial findings. These initial findings can help the government takes quick steps to avoid social and economic damage which could be enormous if time and adequate data are not put into perspective.

This research work takes into account people's opinions on Twitter (as a large community is created on social media which is limitless to race, region, or country) as people err

Manuscript Received April 15, 2022; Revised 16 May 2022 and Published on June 01, 2022
Swati Ganeshrao Dhoke, *Department of Computer Science & Engineering, Prof. Ram Meghe Institute of Technology & Research, Badnera, Maharashtra, India.* ***Mail Id:*** *swatidhoke07@gmail.com*
Dr. S. R. Gupta, *Department of Computer Science & Engineering, Prof. Ram Meghe Institute of Technology & Research, Badnera, Maharashtra, India.* ***Mail Id:*** *rakale@mitra.ac.in*
Prof. R. A. Kale, *Department of Computer Science & Engineering, Prof. Ram Meghe Institute of Technology & Research, Badnera, Maharashtra, India.* ***Mail Id:*** *guptasql_99@rediffmail.com*

their views and opinions on the effect of covid 19. With machining learning, this research work tables different models to analyze peoples' sentiments.

Contribution of the research

- The main aim of this research is to design a machine learning model for the analysis and classification of tweets of covid 19 according to feelings.
- To classify Twitter data using machine learning classifiers with the proposed feature set.
- To propose a classification algorithm for increasing accuracy and classifying Awareness, Irrelevant, Report, and Treatment tweets for a huge amount of Twitter data.

II. RELATED WORK

Shofiya, C.; (2021) proposed the support vector machine (SVM) algorithm for sentiment classification. Evaluation of performance was measured with a confusion matrix, precision, recall, and F1 measure. Results: This study resulted in the extraction of a total of 629 tweet texts, of which, 40% of tweets exhibited neutral sentiments, followed by 35% of tweets that showed negative sentiments and only 25% of tweets expressed positive sentiments towards social distancing. The SVM algorithm was applied by dissecting the dataset into 80% training and 20% testing data. Performance evaluation resulted in an accuracy of 71%. Upon using tweet texts with only positive and negative sentiment polarity, the accuracy increased to 81%. It was observed that reducing test data by 10% increased the accuracy to 87%. Conclusion: Results showed that an increase in training data increased the performance of the algorithm [1].

Chandra R, Krishna A (2021) presented a framework that employs deep learning-based language models via long short-term memory (LSTM) recurrent neural networks for sentiment analysis during the rise of novel COVID-19 cases in India. The framework features an LSTM language model with a global vector embedding and a state-of-art BERT language model. We review the sentiments expressed for selective months in 2020 which covers the major peak of novel cases in India. Our framework utilizes multi-label sentiment classification where more than one sentiment can be expressed at once. Our results indicate that the majority of the tweets have been positive with high levels of optimism during the rise of the novel COVID-19 cases and the number of tweets significantly lowered towards the peak. We find that the optimistic, annoyed, and joking tweets mostly dominate the monthly tweets with a much lower portion of negative sentiments. The predictions generally indicate that although the majority have been optimistic, a significant group of the population has been annoyed with the way the pandemic was handled by the authorities [2].

Cristian R. Machuca et al (2021). proposed a sentiment analysis of English tweets during the pandemic COVID-19 in 2020. The tweets were classified as positive or negative by applying the Logistic Regression algorithm, using this method, and got a classification accuracy of 78.5% [3].

Rustam F, et. al. (2021) performed Covid-19 tweets sentiment analysis using a supervised machine learning approach. Identification of Covid-19 sentiments from tweets would allow informed decisions for better handling of the current pandemic situation. The used dataset is extracted from Twitter using IDs as provided by the IEEE data port. Tweets are extracted by an in-house built crawler that uses the Tweepy library. The dataset is cleaned using the preprocessing techniques and sentiments are extracted using the TextBlob library. The contribution of this work is the performance evaluation of various machine learning classifiers using our proposed feature set. This set is formed by concatenating the bag-of-words and the term frequency-inverse document frequency. Tweets are classified as positive, neutral, or negative. The performance of classifiers is evaluated on the accuracy, precision, recall, and F1 score [4].

Mujahid, M. (2021), proposed the effectiveness of e-learning by analyzing the sentiments of people about e-learning. Due to the rise of social media as an important mode of communication recently, people's views can be found on platforms such as Twitter, Instagram, Facebook, etc. This study uses a Twitter dataset containing 17,155 tweets about e-learning. Machine learning and deep learning approaches have shown their suitability, capability, and potential for image processing, object detection, and natural language processing tasks and text analysis is no exception. Machine learning approaches have been largely used both for annotation and text and sentiment analysis. Keeping in view the adequacy and efficacy of machine learning models, this study adopts TextBlob, VADER (Valence Aware Dictionary for Sentiment Reasoning), and SentiWordNet to analyze the polarity and subjectivity score of tweets' text. Furthermore, bearing in mind the fact that machine learning models display high classification accuracy, various machine learning models have been used for sentiment classification. Two feature extraction techniques, TF-IDF (Term Frequency-Inverse Document Frequency) and BoW (Bag of Words) have been used to effectively build and evaluate the models [5].

Asad Masood Khattak et. al. (2020), proposed research builds user profiles using Twitter data which is later helpful to provide the user with personalized recommendations. Publicly available tweets are fetched and classified and sentiments expressed in tweets are extracted and normalized. The research uses a domain-specific seed list to classify tweets. Semantic and syntactic analysis of tweets is performed to minimize information loss during the process of tweets classification. After precise classification and sentiment analysis, the system builds user interest-based profiles by analyzing users' posts on Twitter to know about user interests. (e proposed system was tested on a dataset of almost 1 million tweets and was able to classify up to 96% of tweets accurately [6].

Dr. K. B Priya Iyer et. al. (2020), focused on the sentiment analysis of COVID-19 using Twitter data. The analyses are based on machine learning algorithms. This article provides an analysis of how people react to a pandemic outbreak, how much they are aware of the disease and its symptoms, what precautionary measures they are taking, and whether or not people are following the government's guidelines, etc. Understanding the posts on social media pages during a pandemic outbreak allows health agencies and volunteers to better assess and understand the public's insolences, sentiments, and needs to deliver appropriate and effective information [7].

III. Proposed Methodology

During crises such as these, microblogging platforms like Twitter are widely used by affected people to post updates and awareness messages. These crisis-related messages disperse among multiple categories like available facilities, asking for help, warning about a region, information about affected, recovered, injured, or dead people, etc. Extracting important situational updates from a plethora of such messages is a difficult yet important task. Given the importance of topic-specific tweets for a time-critical situational response, the crisis-affected communities and professional responders may benefit from using an automatic system that acts as the link between those who are ready to help and those who need help. We aim to excerpt relevant nuggets of information and assign them informational categories using appropriate machine learning techniques.

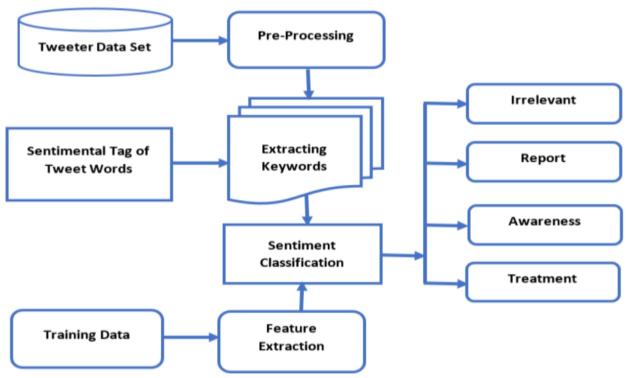

Figure 1: Architecture of Proposed System

Figure 1 shows the proposed architecture of a proposed system for classifying the tweets posted during an epidemic. Following are the step of the proposed system

A. Data Set Description

On Twitter, thousands of updates and opinions regarding this epidemic keep springing up every other day. This study aims to classify the data into relevant labels so that the required information alone can be harnessed. We collected around 1000 tweets (as of 29th March 2020). Though the number of tweets generated is higher, the number of irrelevant tweets was found to be pretty high from the reading, so we constrained the collection to only those tweets having at least 100 likes, 30 retweets, and 30 replies. Basic pre-processing was done to it (such as removal of hyperlinks, mentions, hashtags, emoticons, and out-of-vocabulary words used in social media).

B. Types of Tweets Posted

K Rudra et al, in their own "Classifying information from Microblogs during Epidemics" [4] classified tweets posted during epidemics into the following classes - (i). symptom, (ii). prevention, (iii) transmission, (iv) treatment, (v) death report, and (vi) nondisease.

In this work, the data was thoroughly read to understand the kind of labels that we can use for this model and decided on the below four classes:

1. Reports (Statistics and Government actions)
2. Awareness (Intended for prevention of the spread of epidemic)
3. Treatment (Facilities, Tests, and Medicine)
4. Irrelevant (Everything else)

Table 1: Types and No. of the tweet in the dataset

Type	No. of Tweet
Irrelevant	427
Report	285
Awareness	137
Treatment	72

C. Data Pre-Processing

Feature extraction and pre-processing are crucial steps for text classification applications. In this section, we introduce methods for cleaning text data sets, thus removing implicit noise and allowing for informative featurization. Most text and document data sets contain many unnecessary words such as stop words, misspellings, slang, etc. We have removed all duplicate entries, numbers, special characters, punctuations, and double-spaces and changed the data completely to lower case. Then we have removed all stop words and words with length one.

Inspecting the distribution of data available in each class, we do up-sample wherever necessary. Tokenization is a pre-processing method that breaks a stream of words into words, phrases, or other meaningful elements called tokens. We have tokenized the dataset and found the frequency of occurrence for every token.

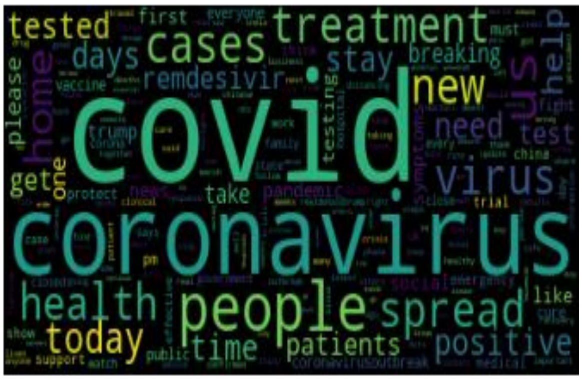

Figure 2: A visual representation of the vocabulary scaled to their frequencies

D. Feature Extraction

N-gram: N-gram is a sequence of words in a sentence. N-gram is probably the simplest concept in machine learning. There are quite some varieties of the usefulness of N-gram. It can be used for autocorrection of words, auto spell check, and also grammar checks. It also helps to check the relationship between words especially when one is trying to figure out what someone is more likely to say to determine the emotions or sentiments through the word said. N-grams are the combination of words that are used together. Unigrams are N-grams with N = 1. For N = 2, these are referred to as bigrams and trigrams for N = 3. N-grams capture the structure of the language helping to determine which word is likely to follow a given word.

The mapping from textual data to real-valued vectors is called feature extraction. An n-gram is a contiguous sequence of n items from a given sample of text. We have used n-gram to find the common words that occur in all four classes and removed them from the dataset as they don't contribute to classification. We have used 1-gram and 2-gram. CountVectorizer is used to transform corpora of text to a vector form of term/token count. We have fit the vectorizer on our corpus for each class separately with an n-gram range of 1 and 2. We have taken the top 10 unigrams (bigrams) from each class and found the intersection and removed them entirely from the corpus.

We have used the Term Frequency - Inverse term frequency technique on the corpus before feeding it into our models. Inverse Document Frequency (IDF) is a method used in conjunction with the term frequency (TF) to lessen the implicitly common words in the corpus. IDF assigns a higher weight to words with either high or low frequencies in the document.

This combination of TF and IDF is well known as Term Frequency-Inverse document frequency (TF-IDF).

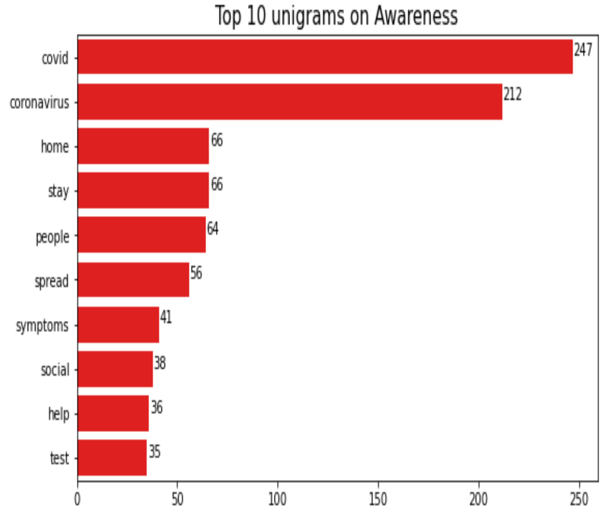

Figure 3: Top 10 unigrams on Awareness

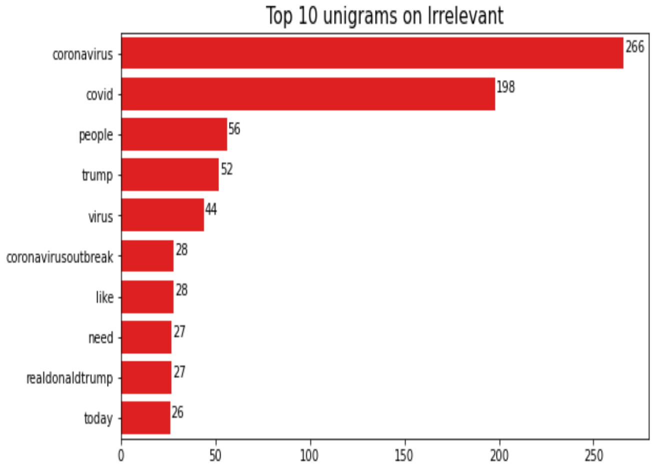

Figure 4: Top 10 unigrams on Irrelevant

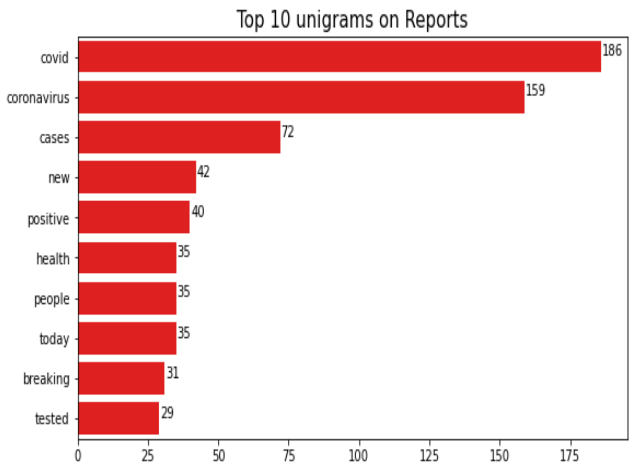

Figure 5: Top 10 unigrams on Reports

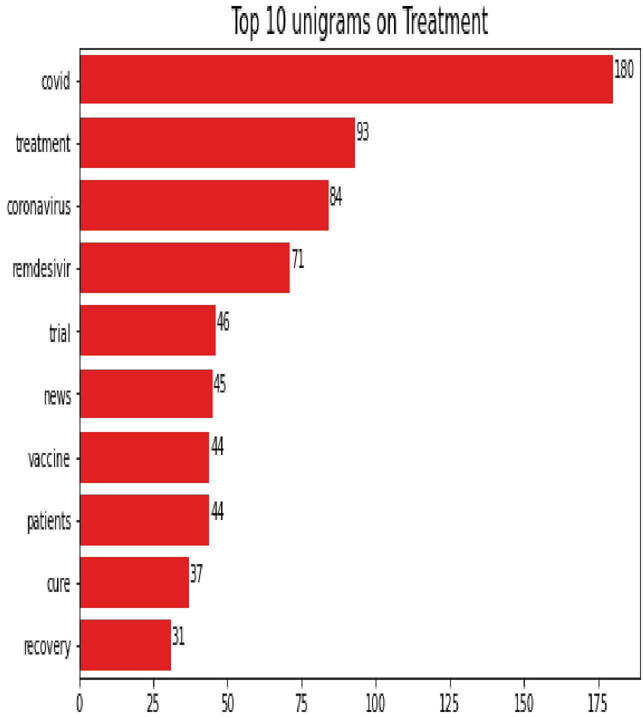

Figure 6: Top 10 unigrams on Treatment

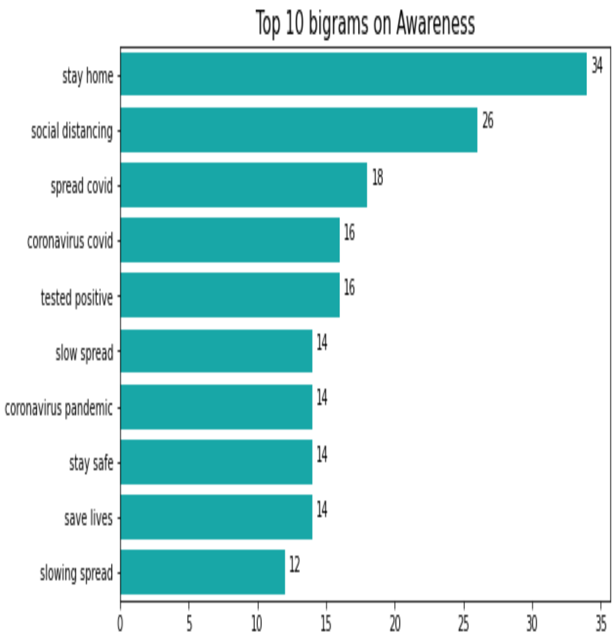

Figure 7: Top 10 Bigrams on Awareness

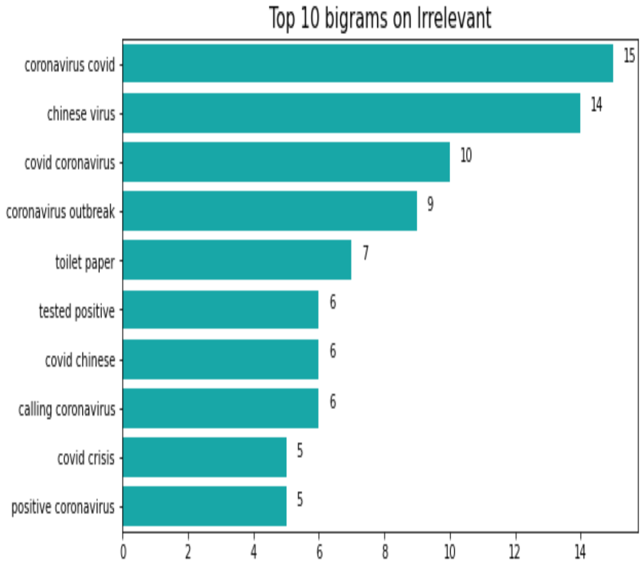

Figure 8: Top 10 Bigrams on Irrelevant

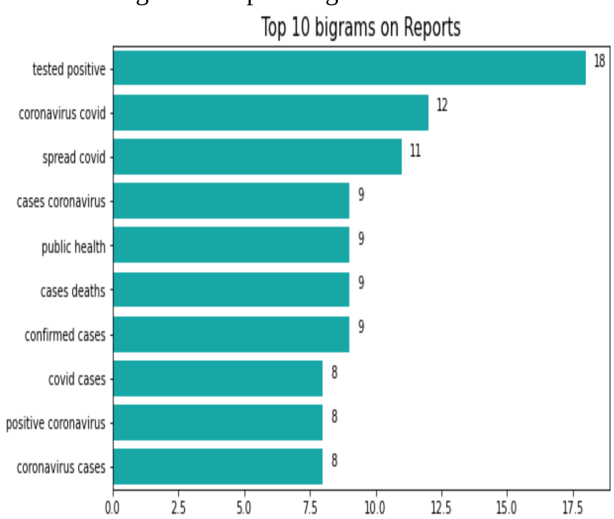

Figure 9: Top 10 Bigrams on Reports

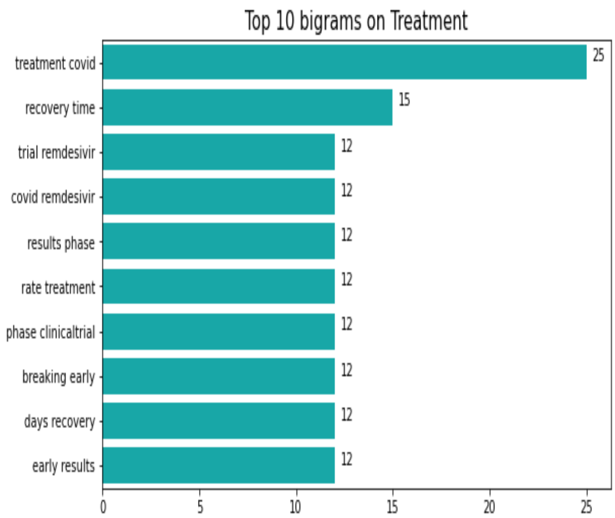

Figure 10: Top 10 Bigrams on Treatment

E. Model Selection

For these experiments, we consider the state-of-the-art models of supervised learning and compare the performances of each. Given that the data after the preprocessing steps are still in a string format, we need to get their word embeddings to carry out the experiments. To suit the needs of our data, we take the help of two mechanisms to get the task done easier and more efficiently: Pipelining and Grid Search.
Pipelining in Python
In any Machine learning problem statement, there is usually a fixed sequence of steps involved. Pipelining aims to chain the multiple steps into one and thus, automate the process. Some codes are meant to transform features- say, normalizing numerical or turning text into vectors, those kinds are the transformers. Other codes are meant to predict variables by fitting an algorithm such as a random forest or support vector machine, those are the estimators.
So, in a pipeline, it first sequentially applies a list of transformers (data modeling) and then a final estimator (ML model). It is a part of the scikit-learn library.

Grid Search in Python: Grid search is used to perform hyperparameter tuning to determine the optimal values for a given model. The value to stipulate the hyperparameter that gives maximum accuracy is a very important factor in determining the result, and here Grid Search CV of the sci-kit-learn library does the same efficiently.

The chosen models
Count Vectoriser and Logistic Regression: Count vectorizing and then a logistic regression model was fed to the pipeline in that order, using the lib-linear library for the latter, and an n-gram range of (1,1), (2,2), and (1,3) for the former.

Tfidf Vectoriser and Logistic Regression: The above models were pipelined and experimented with different ranges of parameters for tuning.

Tfidf Vectoriser and Multinomial Naive Bayes: Following the Tfidf embedding, a multinomial Naive Bayes model was deployed. The advantage of this model is that it specifically works well for text embeddings. Unlike the simple naive Bayes modeling of a document based on the presence and absence of some words, multinomial naive Bayes explicitly models the word counts and adjusts the underlying calculations to deal with it.

Count Vectoriser and Multinomial Naive Bayes: Keeping in mind the advantages mentioned above for the multinomial NB model, we try leveraging it again, but with a count vectorizer as a prerequisite. Parameters were adjusted accordingly.

TfidVectoriser and Stochastic Gradient Classifier: Further experimented with using the SGD Classifier for the data taking a squared loss and experimented over a range of suitable alpha values.

Voting Classifier: A Voting Classifier is a machine learning model that trains on an ensemble of numerous models and predicts an output (class) based on the highest probability of chosen class as the output.
It simply aggregates the findings of each classifier passed into Voting Classifier and predicts the output class based on the highest majority of voting. The idea is instead of creating separate dedicated models and finding the accuracy for each of them, we create a single model which trains by these models and predicts output based on their combined majority of voting for each output class.

IV. RESULT ANALYSIS

The extraction of data from Twitter is carried out and the data is preprocessed as discussed in Chapter 4. The preprocessed data is fed into different types of natural language processing models for statistical text features. The data is further fed into different text feature selection methods to select the best features from the datasets that will provide relevant and accurate results. Feature Selection is the process of filtering irrelevant from the dataset. If the right subset is chosen, it improves the accuracy of the model and helps the model train its data faster. Some of the feature selection methods utilized are CountVectorizer & Logistic Regression, TfidfVectorize & Logistic Regression, CountVectorizer & MultinomialNB, TfidfVectorizer & MultinomialNB, TfidVectoriser and SGDClassifier, Keras Sequential, Voting Classifier.

A. Performance Metrics

This section presents the experimental results and performance metrics for different models. Accuracy is one of the common performance metrics. It is the measure of all the correctly identified cases. It is mostly used when all the classes are equally important. Accuracy is the proportion of correctly classified examples to the total number of examples, while the error rate is incorrectly classified instead of correctly.

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

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Where TP is True-positive, TN is True-negative, FP is False-positive and FN is False-negative. The Seven models have yielded different accuracy scores, which are displayed in table 2.

Table 2: Accuracy Score of various Models

International Journal of Research in Computer & Information Technology (IJRCIT),
Vol.7, Issue 3, June 2022
E-ISSN: 2455-3743
Available online at www.ijrcit.co.in

Classifiers	Accuracy in %
CountVectorizer & Logistic Regression	85.60
TfidfVectorize & Logistic Regression	79.54
CountVectorizer & MultinomialNB	82.19
TfidfVectorizer & MultinomialNB	70.83
TfidVectoriser and SGDClassifier	84.46
Keras Sequential	78.78
Voting Classifier (Hard)	81.43

Table 2: Performance Evaluation of CountVectorizer & Logistic Regression

Tweet	Precision	Recall	F1-Score	Support
Awareness	0.90	0.92	0.91	71
Irrelevant	0.75	0.90	0.82	86
Report	0.85	0.61	0.71	57
Treatment	1.00	0.98	0.99	50

Table 3: Performance Evaluation of TfidfVectorize & Logistic Regression

Tweet	Precision	Recall	F1-Score	Support
Awareness	0.94	0.83	0.88	71
Irrelevant	0.71	0.92	0.80	86
Report	067	0.60	0.63	57
Treatment	1.00	0.76	0.86	50

Table 4: Performance Evaluation of TfidfVectorizer & MultinomialNB

Tweet	Precision	Recall	F1-Score	Support
Awareness	0.84	0.73	0.78	71
Irrelevant	0.64	0.84	0.73	86
Report	0.56	0.60	0.58	57
Treatment	1.00	0.58	0.73	50

Table 5: Performance Evaluation of CountVectorizer & MultinomialNB

Tweet	Precision	Recall	F1-Score	Support
Awareness	0.82	0.97	0.89	71
Irrelevant	0.84	0.72	0.77	86
Report	0.68	0.68	0.68	57
Treatment	0.96	0.94	0.95	50

Table 6: Performance Evaluation of TfidVectoriser and SGDClassifier

Tweet	Precision	Recall	F1-Score	Support
Awareness	0.92	0.94	0.93	71
Irrelevant	0.80	0.83	0.81	86
Report	0.70	0.67	0.68	57
Treatment	0.98	0.94	0.96	50

Table 7: Performance Evaluation of Keras Sequential

Tweet	Precision	Recall	F1-Score	Support
Awareness	0.83	0.94	0.88	71
Irrelevant	0.80	0.66	0.73	86
Report	0.67	0.61	0.64	57
Treatment	0.82	0.98	0.89	50

Table 8: Performance Evaluation of Voting Classifier

Tweet	Precision	Recall	F1-Score	Support
Awareness	0.90	0.89	0.89	71
Irrelevant	0.79	0.87	0.83	86
Report	0.75	0.63	0.69	57
Treatment	0.96	0.98	0.97	50

Out of the discussed models, it is evident that CountVectorizer & Logistic Regression yields the highest accuracy score of 85.60% followed by TfidfVectorize & Logistic Regression. Other performance metrics such as Precision, Recall, and F1-score have also been calculated for all the models.

B. *Misclassification of Tweets*

A confusion matrix is a table that is often used to describe the performance of a classification model on a set of test data for which the true values are known. We also display the confusion matrix for the most accurate model with the help of a heatmap.

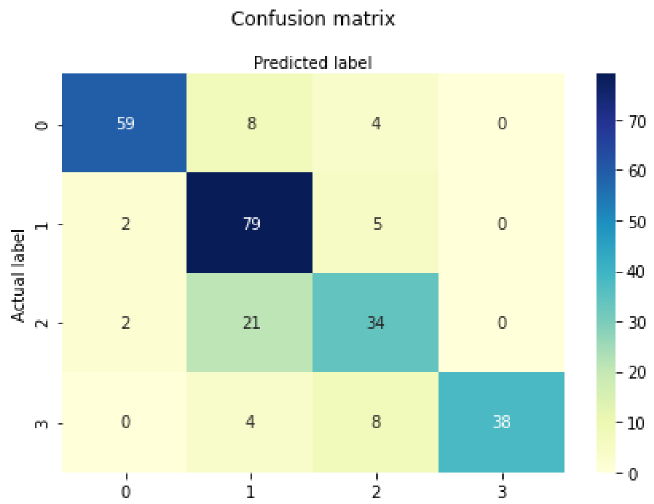

Figure 12: Representation of the best model using the Confusion matrix

Figure 12 shows the confusion matrix, it is evident that more than 13% of the tweets have been misclassified. It is observed that in these classified tweets, the tweets contain information about more than one class like both Reports and Awareness or Reports and Treatment.

Conclusion

Natural Disasters and Epidemics create various kinds of problems for people: physically, mentally, and emotionally. Though this does not have a very direct impact, harnessing the power of Machine Learning is in some way associated with making the situation better, giving how it has become the go-to place for people to rant about their condition, seek help, announce their plan to provide help or spread awareness. Given the vastness and distribution of this data, classifying it also can go a long way in providing even health organizations and NGOs seeking to provide help with relevant information. Out of the discussed models, it is evident that CountVectorizer & Logistic Regression yields the highest accuracy score of 85.60% followed by TfidfVectorize & Logistic Regression.

References

[1] Sofiafiya, C.; Abidi, S. (2021). Sentiment Analysis on COVID-19-Related Social Distancing in Canada Using Twitter Data. Int. J. Environ. Res. Public Health , 18, 5993. https://doi.org/10.3390/ijerph18115993

[2] Chandra R, Krishna A. (2021) COVID-19 sentiment analysis via deep learning during the rise of novel cases. PLoS ONE 16(8): e0255615. https://doi.org/10.1371/journal.pone.0255615

[3] Cristian R. Machuca et al (2021). Twitter Sentiment Analysis on Coronavirus: Machine Learning Approach J. Phys.: Conf. Ser. 1828 012104

[4] Rustam F, Khalid M, Aslam W, Rupapara V, Mehmood A, Choi GS (2021) A performance comparison of supervised machine learning models for Covid-19 tweets sentiment analysis. PLoS ONE 16(2): e0245909. https://doi.org/10.1371/journal.pone.0245909

[5] Mujahid, M.; Lee, E.; Rustam, F.; Washington, P.B.; Ullah, S.; Reshi, A.A.; Ashraf, I. (2021). Sentiment Analysis and Topic Modeling on Tweets about Online Education during COVID-19. Appl. Sci., 11, 8438. https://doi.org/ 10.3390/app11188438

[6] Asad Masood Khattak, Rabia Batool, Fahad Ahmed Satti, Jamil Hussain, Wajahat Ali Khan, Adil Mehmood Khan, Bashir Hayat, "Tweets Classification and Sentiment Analysis for Personalized Tweets Recommendation", Complexity, vol. 2020, Article ID 8892552, 11 pages, 2020. https://doi.org/10.1155/2020/8892552

[7] Dr. K B Priya Iyer, Dr. Sakthi Kumaresh, "Twitter Sentiment Analysis On Coronavirus Outbreak Using Machine Learning Algorithms", European Journal of Molecular & Clinical Medicine, Volume 07, Issue 03, 2020

[8] S. Banik, A. Ghosh, S. Banik, and A. Mukherjee, "Classification of COVID19 Tweets based on Sentimental Analysis," 2021 International Conference on Computer Communication and Informatics (ICCCI), 2021, pp. 1-7, DOI: 10.1109/ICCCI50826.2021.9402540.

[9] Mohammad Abu Kausar, Arockiasamy Soosaimanickam, Mohammad Nasar, "Public Sentiment Analysis on Twitter Data during COVID-19 Outbreak", International Journal of Advanced Computer Science and Applications, Vol. 12, No. 2, 2021

[10] Ahmed MS, Aurpa TT, Anwar MM (2021) Detecting sentiment dynamics and clusters of Twitter users for trending topics in COVID-19 pandemic. PLoS ONE 16(8): e0253300. https://doi.org/10.1371/journal.pone.0253300

[11] Chakraborty, K., Bhatia, S., Bhattacharyya, S., Platos, J., Bag, R., & Hassanien, A. E. (2020). 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, 106754. https://doi.org/10.1016/j.asoc.2020.106754

[12] Cuomo, R.E., Purushothaman, V., Li, J. et al. A longitudinal and geospatial analysis of COVID-19 tweets during the early outbreak period in the United States. BMC Public Health 21, 793 (2021). https://doi.org/10.1186/s12889-021-10827-4

[13] Lamsal, R. Design, and analysis of a large-scale COVID-19 tweets dataset. Appl Intell 51, 2790–2804 (2021). https://doi.org/10.1007/s10489-020-02029-z

[14] Samuel, J., Ali, G. G. Md. N., Rahman, Md. M., Esawi, E., & Samuel, Y. (2020). COVID-19 Public Sentiment Insights and Machine Learning for Tweets Classification. Information, 11(6), 314. MDPI AG. Retrieved from http://dx.doi.org/10.3390/info11060314

[15] Azeez, Nureni & Ogunlusi, Victor & Uloko, Emmanuel. (2021). Sentiment Analysis Of Covid-19 Tweets. Fudma Journal Of Sciences. 5. 566-576. 10.33003/fjs-2021-0501-690.

[16] Xiongwei Zhang, Hager Saleh, Eman M. G. Younis, Radhya Sahal, Abdelmgeid A. Ali, "Predicting Coronavirus Pandemic in Real-Time Using Machine Learning and Big Data Streaming System", Complexity, vol. 2020, Article ID 6688912, 10 pages, 2020. https://doi.org/10.1155/2020/6688912

[17] Cristian R. Machuca, Cristian Gallardo and Renato M. Toasa, "Twitter Sentiment Analysis on Coronavirus: Machine Learning Approach", J. Phys.: Conf. Ser. 1828 012104

[18] Giulia Pes, Angelica Lo Duca, Andrea Marchetti, "Towards a Sentiment Analysis of Tweets from Online Newspapers Regarding the Coronavirus Pandemic", HighTech and Innovation Journal, Vol. 2, No. 4, December 2021

[19] Scikit-learn: Machine Learning in Python, Pedregosa, et al., JMLR 12, pp. 2825-2830, 2011i.