Disaster Related Tweets Analysis with Machine Learning Approaches

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***Abstract*— It's no secret that the microblogging service Twitter (X) has quickly risen to prominence as one of the most reliable places to get the latest updates on breaking events. Tweets, Twitter's information streams, are sent out voluntarily by registered users and can reach even non-registered users, often before more conventional sources of mass news. In this research, we use machine learning to create models that can find helpful tweets on disasters automatically. Social media users provide massive amounts of data during natural catastrophe situations, some of which are useful for relief operations and emergency management. In this work, we analyze the material shared on social media during two hurricanes and one earthquake. This research has shown a machine-learning approach to categorizing tweets in relation to disasters and labeling Twitter data. This study has applied five machine learning algorithms to predict disaster and non-disaster tweets. In our model and among these five machine learning algorithms three perform similarly but Logistic Regression has achieved the best 80.5% model accuracy among all other algorithms.**

Keywords*— *disaster texts, tweet analysis, machine learning, logistic regression

I. Introduction

In the lead-up to, during, and after catastrophes, social media has become an invaluable resource for understanding people's actions, decisions, and information-gathering methods. Social media is frequently used by the public, first responders, and weather organizations to communicate during and after a catastrophe. Twitter is the ideal location to find out 'What's Happening' in real time, especially in light of recent natural disasters like typhoons, floods, tornadoes, and earthquakes [1]. Using Twitter to monitor the progress of a crisis and notify authorities of hotspots where relief is needed has been demonstrated to be useful in recent studies [2].

In the aftermath of a natural or man-made catastrophe, it is crucial for rescue and assistance groups to act quickly to help the victims. Professional humanitarian groups and government agencies face significant challenges in this endeavor due to factors such as victims' inaccurate position information, an overwhelming number of rescue-related contacts, and the need to priorities rescue activities based on victims' requirements [3]. The reaction time in these situations is lengthened by the absence of relevant information. It has been discovered that during times of crisis, social media sites like Twitter and Facebook see a dramatic increase in the volume of user-generated content. People frequently use these channels to update their situation, record casualties and building damage, and solicit aid.

In the event of a catastrophe [4], this user-generated content from social networking sites can be used to organize rescue efforts and give people a greater understanding of the situation. Numerous accounts in the media have attested to the significance of social media in catastrophe relief, facilitating the discovery of aid, and even saving lives. For instance, during Storm Harvey [5], a lady was saved after tweeting for help when the standard emergency number was inaccessible. Social media platforms like Twitter are often the first source of information during a disaster or crisis. Machine learning algorithms can quickly analyze large volumes of tweets to identify critical information such as the location and severity of the disaster, the number of people affected, and the level of urgency.

Machine learning algorithms can detect early warning signs of calamities and crises by analyzing patterns and trends in tweets [6]. This can assist authorities in taking proactive measures to mitigate the disaster's effects and save lives. Situational awareness is essential for emergency responders to make informed decisions during a disaster. The analysis of real-time tweets by machine learning can provide a comprehensive picture of the situation on the ground, including the requirements of the afflicted population, the availability of resources, and the progress of response efforts. There is frequently an abundance of information, making it difficult for emergency responders to prioritize and act upon the most important data. Machine learning can aid in identifying and filtering relevant data, providing real-time actionable insights to responders. In this research we have applied machine learning algorithms to detect the tweet disaster or non-disaster.

The purpose of machine learning research on disaster-related tweets is to enhance emergency response efforts and save lives during disasters and crises. Social media platforms like Twitter provide a multitude of real-time data that can be analyzed to provide emergency responders with vital insights. Algorithms capable of machine learning can rapidly process large volumes of tweets to identify patterns and trends, allowing authorities to take preventative measures and respond more effectively. This research seeks to provide a quicker, more accurate, and more efficient method of

analyzing disaster-related tweets in order to enhance emergency response efforts and, ultimately, save lives.
The rationale for the study is that traditional disaster response methods frequently rely on limited and out-of-date data, making it difficult for emergency responders to make informed decisions. Twitter and other social media platforms offer a vast and real-time source of information that can enhance situational awareness and response efforts. Nevertheless, manually analyzing large volumes of tweets is a daunting task, and it can be difficult to discern relevant information amidst the noise. Machine learning offers a remedy by automating the analysis of texts and the identification of crucial information. This study aims to investigate the potential of machine learning algorithms for analyzing tweets related to disasters in order to enhance emergency response efforts and ultimately save lives.

II. Literature Review

For disaster-related tweet analysis by machine learning research, background study is crucial because it offers a thorough grasp of the body of literature, knowledge gaps, and potential difficulties in this area. Researchers can evaluate the efficacy of current methods, find the most important information that can be extracted from disaster-related tweets, and create novel solutions by conducting a thorough background investigation. A more complete picture of the potential advantages and difficulties of using machine learning algorithms for disaster-related tweet analysis is provided by background research, which also aids in identifying ethical considerations and possible biases in the data. All things considered, a comprehensive background investigation is essential for guiding the research design, methodology, and anticipated results of disaster-related tweet analysis by machine learning research.
When a natural catastrophe strikes, there are frequently a significant number of tweets shared on Twitter. A significant portion of the tweets that are posted in [7] response to a catastrophe is typically unconnected and irrelevant. Some people take advantage of current events and trends that are trending high in popularity in order to attract users of Twitter to their tweets or accounts without any intention of providing educational or helpful methods or information concerning the catastrophe event that is taking place.
According to Olteanu [8], there are three broad groups into which news coverage of natural disasters can be placed: related and instructive; related but not informative; and unrelated. Since recognizing communication occurs in disaster scenario is a difficult endeavor that calls for a detailed investigation of the significance of the information and its dimensions like freshness, location, freshness, and the scope of the disaster, the authors of this [8] paper limit their attention to the identification of tweets related to disasters.
Tweets about disasters have been identified using supervised machine learning methods according to Habdank et al., [9] Most supervised machine learning methods in this space make use of linguistic and other statistical characteristics unique to each tweet, such as the tweet's part of speech, user references, duration, number of hashtags, etc.
In [10], Huang introduced a coding scheme for topicalizing tweets in accordance with catastrophe severity. During Hurricane Sandy, they compiled comments and removed any that didn't pertain to the storm. Hashtags like "breakingstorm," "superstorms," "hurricanesandyproblems," and "njpower" that were used in relation to Hurricane Sandy were pulled from the data. A text was not considered to be related to Hurricane Sandy if it did not include a set of terms in either the content or the hashtag. After collecting the pertinent tweets, they investigated a selection of 2000 of them for characteristics and individually annotated them into categories.
During times of crisis, Xukun et al., [11] employed a clustering algorithm that was founded on syntactic similarity to identify geo-located communities on Twitter. Herfort discovered a connection between the locations of messages on social media platforms and the geographical characteristics of flood occurrences.
Other researchers [12] have extracted themes and made categories from social media texts in order to advance our understanding of crisis situations, complementing the research that emphasizes the geographic and temporal features of social media. To train machine learning models to categorize useful tweets and extract disaster-relevant information, Imran compiled human-annotated Twitter corpora gathered during 19 distinct crises. Wang combed through tweets about wildfires to find key words people were talking about. Ye [13] sorted "dengue"-related posts on Weibo into five distinct groups and studied the correlation between online conversations about the illness and its spread. Table I shows the comparison between different works related to this research.

TABLE I. Comparison Table Between Different works

Ref	Contributions	Dataset	Algorithms	Best Accuracy
[14]	Classifying tweets during emergencies using machine learning models	Kaggle	SVM, Bi-LSTM	88%
[15]	Machine learning-based categorization of tweets on natural disasters	Own Dataset	BNB, MNB, LR, KNN, DT, and RF	87%
[16]	Predicting Disaster Tweets	Social Media	BERT	90%
[17]	Classification of Disaster Specific Tweets	Own Dataset from Twitter	NB, LR, J48, RF, and SVM	88%
[18]	Tweet Classification of the Earthquake Disaster Situation	Own	SVM, NB	81%

III. Proposed Methodology

Data collection, data preprocessing, feature extraction, training of machine learning algorithms, and assessment of models are all essential parts of any research approach. During this stage, we gather tweets from social media sites like Twitter that discuss catastrophes or other emergencies. The gathered data undergoes a series of transformations in the data preprocessing step to make it more amenable to machine learning methods. Features, like the existence of a certain phrase or hashtag, are extracted from the preprocessed data in the feature extraction step. The extracted characteristics are put to use in the training portion of the machine learning program. Accuracy and precision are just a couple of the measures used to assess the model's performance.

A. *Data Collection*

Finding an appropriate dataset was the first step in our data collection process. The fields for ID, keyword, location, text, and target were extracted from Twitter (X) containing 7,580 tweets about catastrophes or crises. If the message pertained to a crisis, it would be marked as such in the designated pitch. Both the location and the disaster-related term, such as "crash," "quarantine," or "bush fires," are included in the file. The tweets were then manually sorted into those discussing actual disasters and those discussing other topics (such as puns on the term or movie reviews). We then removed any tweets that were duplicates, were not pertinent, or were written in a language other than English from the dataset. They also deleted tweets that had nothing to do with emergencies or catastrophes. Fig. 1 and Fig. 2 provide insightful data on the relationship between disaster and non-disaster tweets. In Fig. 1, the ratio between disaster and non-disaster tweets is examined, shedding light on the prevalence and importance of disaster-related content in social media. This ratio could offer valuable insights into public sentiment and awareness regarding disasters. Fig. 2, on the other hand, explores the average word length in tweets, which can be indicative of communication style and the level of detail in disaster-related discussions. Together, these figures offer a comprehensive view of how social media users engage with and communicate about disasters, facilitating a better understanding of public discourse in times of crisis.

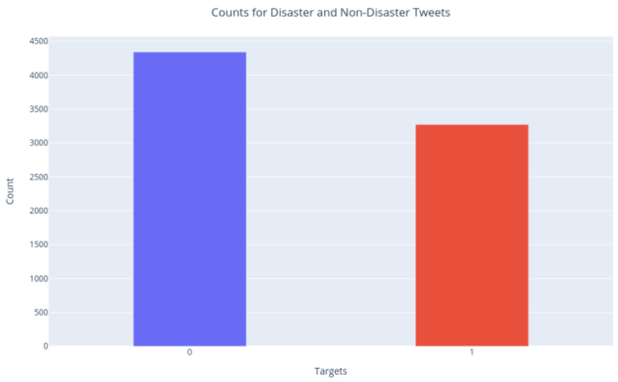

Fig.1. Ratio between disaster and non-disaster tweets

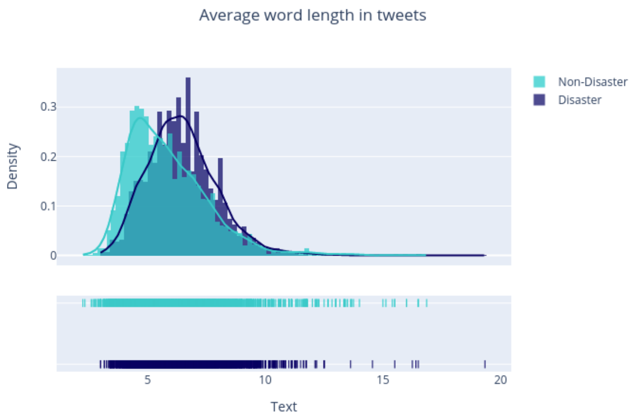

Fig.2. Average word length in tweets

B. *Data Pre-Processing*

The data preprocessing techniques has been used in the disaster-related tweet analysis by machine learning research are critical to the accuracy and reliability of the results. Let's examine each of these techniques in more detail:

Tokenization involves breaking down text into individual words, phrases, or symbols to create tokens. This technique helps to reduce the dimensionality of the data and provides a basis for feature extraction [19]. The researchers likely used a tokenizer library such as NLTK [20] to tokenize the tweet text.

Stopword removal is the process of removing commonly used words (e.g., "the," "and," "of") that do not add meaning to the text [21]. This technique helps to reduce noise in the data and allows the machine learning algorithm to focus on important words and phrases. The researchers likely used a stopword removal library such as NLTK to remove stopwords from the tweet text.

Stemming is the process of reducing words to their base or root form (e.g., "running" to "run"). This technique helps to reduce the dimensionality of the data and ensure consistency in the text [22]. The researchers likely used a stemming library such as NLTK or PorterStemmer to stem the tweet text.

Lemmatization is the process of reducing words to their base or dictionary form (e.g., "better" to "good") [23]. This technique is similar to stemming but results in more meaningful base words. The researchers likely used a lemmatization library such as WordNetLemmatizer to lemmatize the tweet text.

C. *Proposed Model Workflow*

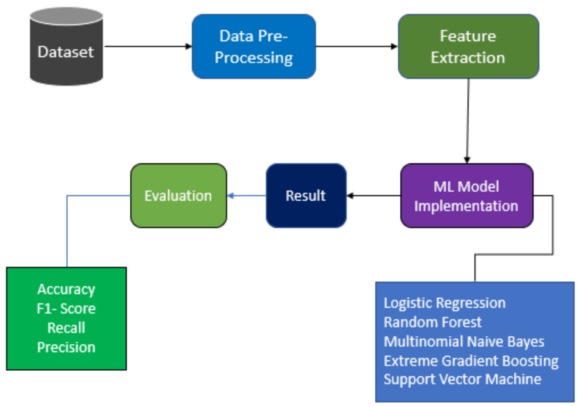

Fig.3. Proposed model of workflow

D. *Machine Learning Model*

By identifying patterns and relationships within the tweet data, machine learning algorithms can address the problem of tweet analysis related to disasters. Specifically, supervised learning algorithms can be trained on a labelled dataset of disaster-related and non-disaster-related tweets to learn to differentiate between the two classes. Once trained, these algorithms can classify unlabeled tweets as either disaster-related or non-disaster-related. The classification accuracy can be measured using performance metrics such as precision, recall, and F_1-score.

1) *Logistic Regression (LR)*

The likelihood of an objective variable can be predicted using logistic regression, a supervised learning categorization method. This implies that there are only two potential categories for the dependent or target variable. In layman's terms: the dependent variable is of a binary type, with information written as either 1 (for achievement) or 0 (for failure). Logistic regression models are used in mathematics to make predictions about P(Y=1) as a consequence of X. Spam identification, Diabetes prediction, cancer detection, and so on can all benefit from this remarkably straightforward machine learning (ML) method. Recent applications of logistic regression in Circulation include a meta-analysis assessing the association between the TaqlB genetic makeup and risk of cardiovascular disease, an analysis of gender as a predictor of operative mortality following coronary artery bypass grafting, and several other applications [24].

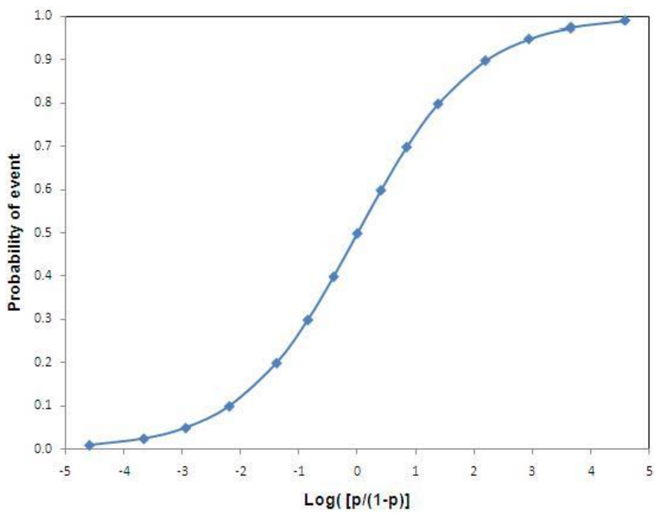

Fig.4. Logistic Regression curve example [25]

2) *Multinomial Naive Bayes (MNB)*

The Multinomial Naive Bayes [26] approach is a popular Bayesian learning strategy (NLP) in the field of Natural Language Processing. The program uses the Bayes theorem to make a label prediction for a document like an email or news story. It calculates the likelihood of each tag for a given sample and provides the tag with the highest likelihood. Since the characteristics being categorized are not reliant on one another, the Naive Bayes classifier is a collection of distinct algorithms that have this property. The presence or lack of a feature does not determine the presence or absence of any other feature. It works based on the below equation (1):

$$P(A|B) = P(A) * \frac{P(B|A)}{P(B)} \qquad (1)$$

Here, PA is the prior probability of the occurrence of event A, which means it is the probability of A happening before taking into account any additional information or factors. PBA is the conditional probability of event B occurring given that event A has already occurred. In other words, PBA is the probability of event B given that we know event A has happened. PAB is the conditional probability of event A occurring given that event B has already occurred. In other words, PAB is the probability of event A given that we know event B has happened. PB is the probability of the occurrence of event B, which means it is the probability of B happening before taking into account any additional information or factors [26].

3) *Extreme Gradient Boosting (XGB)*

The technique known as "Extreme Gradient Boosting" [27] is one of the most common boosting methods. The precision of gradient boosting is improved by employing consecutive predictors, each of which attempts to rectify the errors caused by the one that came before it. Instead of modifying the weights of the training cases, as Adaboost does, each predictor in this method is trained using the residual mistakes of the predecessor as labels. This is in contrast to Adaboost, which uses the weights of the training cases. For instance, the Gradient Boosted Trees technique relies on CART as its underpinning (Regression Trees) [28]. In gradient boosting frameworks, the technique known as XGBoost is frequently utilized. This method takes the form of an aggregation decision tree strategy. Although decision trees appear obvious at first glimpse, it may be more difficult to acquire a first-hand comprehension of earlier tree-based algorithms.

Fig.5. Gradient Boosting visualization

4) *Random Forest (LR)*

The framework of a random forest is precisely what the name implies: it is an ensemble of many individual decision trees. Each individual tree in a random forest makes a classification prediction, with the most widely held classification being utilized to make the ultimate prediction [29]. The key is to have only a small amount of overlap amongst models. An ensemble of uncorrelated models can provide more reliable predictions than any one of them, just like an assortment of low-correlated assets (like stocks and bonds) does. Random Forest, developed by Leo Breiman and Adele Cutler [30], is a patented computer learning method that aggregates the predictions from many decision trees. The ease with which it handles both classification and regression problems has led to its widespread use.

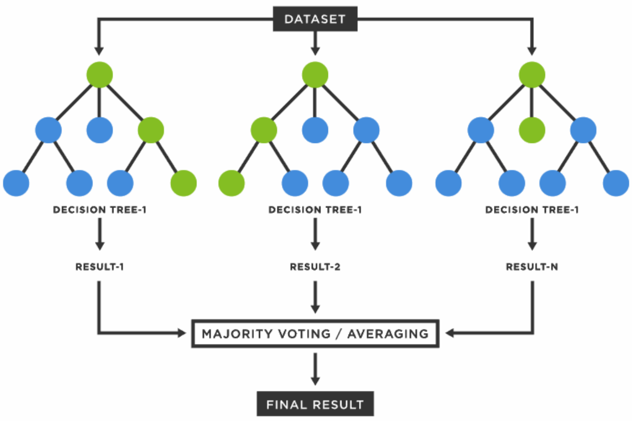

Fig.6. Random Forest visualization

5) Support Vector Machine (SVM)

A common supervised learning method, Support Vector Machine (SVM) [31] is applied to problems involving categorization and regression. In SVM, we look for a good judgment boundary or hyperplane that divides the data into distinct groups. To find the best hyperplane to optimize the gap between the classes is SVM's central concept. The margin is the furthest data point away from the hyperplane in each category. The hyperplane with the largest range is chosen by SVM because it is thought to be more adaptable to novel, unknown data. Both linear and non-linear categorization issues are amenable to SVM's use. SVM identifies the hyperplane that divides the data into groups when the data can be separated into such classes linearly. The SVM employs a kernel technique to move the data into a higher dimensional space, where it may become linearly separable, if the data is not already. Linear, quadratic, and radial basis function (RBF) kernels are the most popular types.

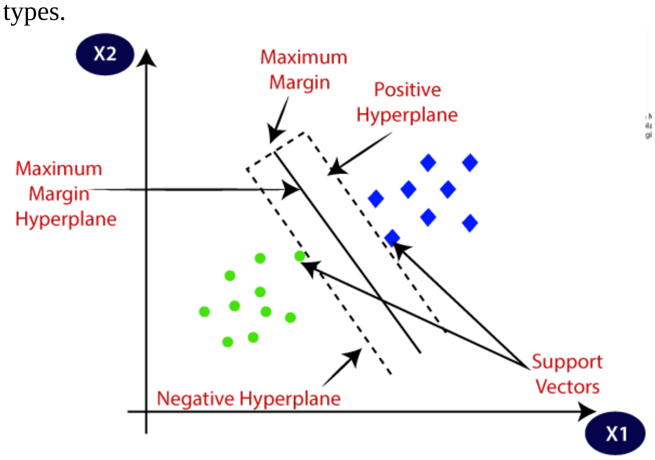

Fig.7. Support Vector Machine graph [32]

IV. EXPERIMENTAL RESULT

Many people make mistakes when training or when projecting results. There is a correlation between model complexity and training error rate; as model complexity rises, training mistakes fall. The Bias-Variance Decomposition (Bias + Variance) method can help reduce the number of times that correct generalizations are made. Overfitting occurs when attempts to reduce training errors contribute to rises in test errors. To evaluate a classification system, one can look at metrics like the F_1-Score, recall, precision, and accuracy.

A wide range of techniques was used by the writers to evaluate the efficacy of their models. For the purpose of performance assessment, some studies used multiple markers, while others used only one. Accuracy, precision, memory, and F_1-Score are used to evaluate the efficiency of this task. As a paradigm for analyzing forecast data, this four-factor model is quite effective.

The capacity to appropriately recognize and categorize incidents is related to accuracy.

Equation 2 shows the formula of accuracy [33].

$$Accuracy = (TP + TN)/(TP + FP + TN + FN) \quad (2)$$

Specifically, accuracy in statistics is defined as the ratio of actual positive occurrences to the total predicted positive events. The mathematical expression of accuracy is given by Equation 3 [34].

$$Precision = TP/(TP + FP) \quad (3)$$

How successfully the algorithm is able to identify persons who have cancer is quantified by a metric called "recall" [35]. Mathematically, recall is represented by Equation 4.

$$Recall = TP/(TP + FN) \quad (4)$$

The term "harmonic mean" describes this method since it balances accuracy and memory. A version of the mathematical equation for the F_1- Score [35] is given by Equation 5.

$$F_1 - Score = 2((Precision \times Recall)/(Precision + Recall)) \quad (5)$$

A. Result

In this study, we have used five machine-learning algorithms to analyze the disaster-related tweets. Among five algorithms, LR, MNB, and SVM works similarly but LR achieved the best 80.5% model accuracy among these five algorithms. XGB performs poor in this model. It has achieved 73% accuracy. Finally, RF got 79% accuracy which is good. Table II shows the classification report of the model.

TABLE II. CLASSIFICATION REPORT OF THE MODEL

Algorithms	Precision	Recall	$F_1 - $ Score	Accuracy
LR	0.80	0.88	0.84	80.5%
MNB	0.78	0.91	0.84	80.3%
RF	0.77	0.90	0.83	79%
XGB	0.69	0.92	0.79	73%
SVM	0.80	0.88	0.84	80.4%

In Fig.8, AUC comparison of five machine learning algorithm has been shown.

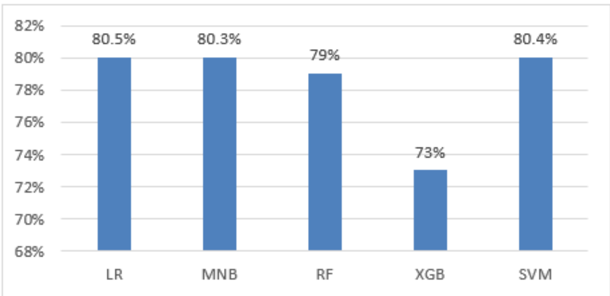

Fig. 8. AUC comparison of five machine learning algorithm.

V. DISCUSSION

In recent years, disaster-related tweet analysis using machine learning algorithms has attracted significant research interest. People now use social media platforms such as Twitter to share information about disasters, including their personal experiences and perspectives. The analysis of disaster-related tweets can assist emergency responders and decision-makers in comprehending the impact of disasters on affected communities, identifying areas requiring urgent attention, and enhancing response strategies. Finding a suitable dataset was the initial phase in our data acquisition procedure. The ID, keyword, location, text, and target fields were extracted from a Kaggle dataset consisting of 7,580 tweets about disasters and crises. If the message pertains to a crisis, the designated pitch will indicate as such. In this study, five machine learning algorithms were used to analyze tweets related to disasters. LR, MNB, and SVM operate similarly among the five algorithms, but LR achieved the highest model accuracy of 80.5% among these five algorithms. XGB performs poorly according to this paradigm. It attained 73% precision. Ultimately, RF's accuracy was 79%, which is excellent. In the result part we have showed the classification report and confusion matrix of all the machine learning algorithms.

VI. CONCLUSIONS AND FUTURE WORK

Machine learning algorithms can be used to analyze tweets about disasters by employing techniques like mood analysis and subject modeling. First responders and policymakers can use this information to refine their reaction plans. The creation of real-time crisis reaction systems, as well as the identification and categorization of misinformation in tweets about disasters, are two examples of potential uses. In this study, we look at the content posted online during three natural disasters: two cyclones and an earthquake. In this study, we demonstrate a machine-learning technique for classifying Twitter data and labeling tweets in connection to natural catastrophes. Five different machine learning algorithms are used to make predictions about Twitter before and after a disaster occurs. Three of the five machine learning algorithms we used to build this model work equally, but Logistic Regression had the highest accuracy at 80.5%. Accuracy is one of the crucial limitations of this work. It must be improved in our future work. Data should be collected more accurately. These two scopes are open for future researchers. In future we are considering below implications:

- Will implement this work with deep learning
- Will try to collect a more accurate dataset
- Will try to create better classification models.
- Will improve accuracy.

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