Classification of Tweet on Disaster Management Using Random Forest

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Abstract. The disaster management is highly responsible for managing the evacuation and deploying rescue teams to reduce the loss of lives and properties. However, it is considered challenging to obtain accurate information in timely fashion from various regions of the affected zones. With the advent of social media and networks, the information dissemination on such events can sense wide information from different zones but the information is in unstructured form. It is hence necessary to acquire correct or relevant information relating to that event. In this paper, we utilize random forest (RF) model to effectively classify the information from tweets (twitter.org) to find the location in case of a natural disaster. The proposed classification engine involves the collects of tweets, pre-processing of texts, RF classification and the extraction of location and determination. The classification is made effective using a pre-trained word vectors that includes the crisis words and global vectors for word representation (GLoVe). This pre-training captures the semantic meaning from the input tweets. Finally, extraction is performed to increase the accuracy of the model and in addition it determines the location of the disaster. The experiments are conducted on a real datasets from recent hurricanes. The results of simulation shows that the RF performs in a better way than other existing models in terms of accuracy, recall, precision and F1-score. It is seen that RF classifies effectively the tweets and analyses the accurate location.

Keywords: Machine learning · Classification · Tweet · Disaster management · Word

1 Introduction

The exponential growth of social media, such as Twitter and Facebook, is being massively adapted in several applications. Social media has extended its role to, but not limited to, the analysis and detection of health and disease [1], the quantification of controversial information [2] and the management of disasters [3, 4]. Natural disasters frequently disrupt regular communication due to damaged infrastructures [5], resulting in information outflow.

A Hurricane Sandy report [6] shows that more people communicate through social media. People sought help promptly and quickly, seeking information on transportation, shelter, and food, while trying to get better communication via family/friends in and

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out of the disaster region. This makes it more beneficial to manage a natural disaster by means of the huge information flow across social media. Twitter demonstrated its utility during Hurricane Sandy, and it again played an important role in restoration, donations, and recovery following Hurricanes Harvey and Irma.

Social media allows individuals in the areas concerned to publish messages reflecting the exact situation, losses caused and healing status, people needs, status of the operations in rescue and relief, etc. Individuals or associations, on the other hand, can say how they can help or indicate exactly how they can help reduce the effect of the disaster. Although the use of social networks appears to be appealing [7], the majority of applications still lack features and are inoperable. Although social media has enormous potential for crisis response, much of it has yet to be realized. Only recently, work on the use of twitter in emergency situations has begun. Since tweets posted during disasters can include different types of information, the exact information that exists in a given tweet could be identified automatically. It will help to determine if various groups as well as different organizations have different insights into the disaster scenario.

The information in a tweet may be on damage to infrastructure, medical help, medical resources such as drugs, available medical tools, resources such as food, water, clothing, clothing, etc. We want to identify what kind of information the tweet contains when a tweet is posted. Different types of information, such as available resources, infrastructure damage, necessary medical resources etc., are seen in various categories. A single tweet may, in several cases, contain information about several categories of information.

The present study considers mainly the problem associated with automated classification from a tweet a problem of the classification of multiple classes and examine the applicability to this task of different algorithms. The major challenges to this task seem to be due to the informal writing manner and shorter tweet length. For this scenario, we define multiple big data feature sets and evaluate the performance of a variety of classifiers. Besides that, some of these tweets may not be visible because of the variety of aid request tweets. Therefore, an automated classification system is essential for understanding the Twitter context, classifying the specific rescue tweets, giving priority to context-based tweets, and then scheduling rescue missions and allocating appropriate resources.

In this paper, we utilize random forest (RF) model to effectively classify the information from tweets to find the location in case of a natural disaster. The proposed classification engine involves the collects of tweets, pre-processing of texts, RF classification and the extraction of location and determination. The classification is made effective using a pre-trained word vectors that includes the crisis words and global vectors for word representation (GLoVe). This pre-training captures the semantic meaning from the input tweets. Finally, extraction is performed to increase the accuracy of the model and in addition it determines the location of the disaster.

2 Related Works

This section reviews relevant studies on the classification of actionable social media tweets [15–19]. The analysis of actionable tweet content and feelings has gradually been applied in the development of machine learning. Ferrara et al. [8] have applied

Social Media text machine learning technology to detect extreme user interaction. The system has been experimented with a set of over 20,000 tweets generated by Twitter actionable tweet accounts.

To the same effect, [9] is proposed for the classification of actionable tweets as a machine-based training technique. With the classic feature set, the Naïve Bayes is applied. In order to identify which sentimental class is associated with actionable tweet communication, the system is based on the classification of user reviews into positive and negative classes.

Contrary to the work in [8], which mainly focuses on the classification of extremism in skewed data, the NB algorithm is used for balanced data with robust results. The total dependencies of the sentence are not, however, taken into account. This problem can be addressed through the application of machine learning models using word embedding. Researchers have also begun researching several ways to analyze actionable tweets in non-English languages automatically.

Hartung et al. [10] proposed, in this connection, a method of machine learning to detect extreme posts on German Twitter accounts. Various features, such as textual indices and linguistic patterns, are being experimented with. The system produced better results by utilizing cutting-edge technology.

Over 30,000 tweets related to marijuana have been collected by Nguyen et al. [11]. The technique of text mining offers some useful insights into the data obtained. The unsupervised sentiment classification techniques used in Lexicon rely primarily on certain sentimental lexicons and sentiment scoring modules. As with other areas of feeling analysis, Ryan et al. [12] investigated actionable tweet affiliations by proposing a new technique based on sentiment detection and part-of-speech by actionable tweet writers. The system can detect suspect activities online by actionable tweet users in a flexible way.

Chalothorn and Ellman [13] have suggested an analysis of sentiment to analyze radical posts using various lexical resources online. The intensity and class of feelings in the text are calculated. Following the completion of necessary pre-processing tasks, textual information was sent to web forums such as Montada and Qawem, and various feature-driven measures to manipulate and detect the actionable tweet content are used. Experimental results indicate that the forum Montada is better than the forum Qawem. It has been concluded that there are radical posts on the Qawem forum. Another noteworthy task is to collect a large data set of actionable tweet ideologies from [14]. The topics under discussion and categorized into positive and negative classes were studied using different sentiment analysis techniques. In addition, the opinions on tweets expressed by both men and women were also emphasized in terms of sex.

The studies mentioned before have been based on different approaches, like supervised machine training, an approach such as a lexicon and a clustering based and hybrid model for classification of actionable tweets. The applicability of sentiment-based profound learning models to the state of the art in classifying tweets must nevertheless be investigated.

3 Proposed Method

The proposed method involves the process of extracting and classification of actionable tweets using RF classifier. The process of which is illustrated in Fig. 1.

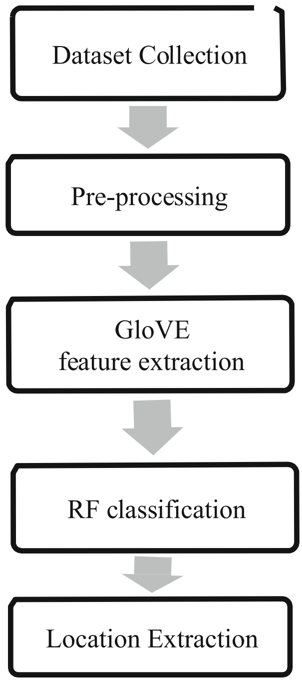

Fig. 1. Proposed framework

3.1 Preprocessing

We have applied various methods of preprocessing, such as tokenization, removal of words, conversion of cases and removal of a special symbol. It further involves acronym expansion [21], removal of non-ASCII characters and smiley [22], case folding, punctuation removal and stop word removal [23], special character removal [24] and phone number or URL handling. The tokenization gives a unique set of tokens (356,242) which contribute to the construction of the vocabulary used to encode the text from the training set.

3.2 Training, Validation and Testing

The dataset was divided into three components: train, test and validate. The training, validation and testing are displayed in Fig. 2.

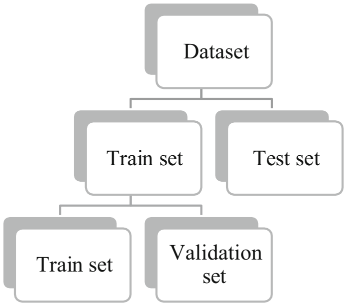

Fig. 2. Training/Testing/Validation set

Training Data: Data for training the model is used, where 80% of the data is used and can vary according to the experimental requirements.

Data Validation: This minimizes the problem of overfitting as often occurs because the accuracy of the training phase is high and the performance against test data is degraded. A total of 10% from the entire datasets is regarded as the validation set, which is thus used by applying parameter tuning to prevent performance mistakes. We used automated dataset monitoring, which ensures an uneven model assessment and minimizes overfitting, for this purpose.

Testing Data: 20% of the entire datasets checks the performance of the trained model with the data not seen. When fully trained, it is used for the model evaluation.

3.3 Feature Extraction

The study uses a pretrained Glove word vectors model for the generation of feature word vectors based on the statistical co-occurrences. The extraction using embedded Glove word vectors model is present in [25], where at the end of each extraction, the model is tested in terms of three different metrics as below:

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

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

$$Specificity = \frac{TN}{TN + FP}$$

The determination of all the three essential metrics helps in valid evaluation of the features extracted thereby eliminating the unwanted words present during the validation of classifier.

3.4 Random Forest Classification

A random forest is a set of decisions, each formed by a sub-sampling of data [20]. The forest is a collective approach. It also adds randomness to the feature selection as well as the training data. It considers the optimal function among the random subsets of features, instead of choosing the best function among all features split into a node. The RF is found by avoiding over fitting via an average model to achieve greater generalization performance. Prediction is done by selecting a class from the individual decision treaties with majority voting. The RF improves the predictability of decision-making trees.

The bagging technique is combined with the random functional selection method. As shown in Fig. 3, the RF algorithm works. The training dataset x is classified by y_i with a n dimension vector. The RF collects a random sample and recurrently builds divisions based on features selection in random manner until the size of the tree matches with the dataset (step 1–5). The rest of the data is removed from the tree in order to obtain the leaf classes. The process of forest construction is repeated several times (step 6–10).

Algorithm:

Step 1: for i : 1 to M //initialization

Step 2: $x \in x_i$

Step 3: forest = forest U Randomized Tree (x)

Step 4: end for

Step 5: Assign each instance to a final category based on a majority vote over forest

$$P(c \mid v) = \frac{1}{T}\sum_{t=1}^{T} P_t(c \mid v)$$

Step 6: Function Randomized Tree (x)

Step 7: While Tree.size<MaxTreesize

Step 8: $f \in F \wedge f = \max$ InformationGain(x)

Step 9: Tree.splitOn(f)

Step 10: Return tree

Fig. 3. Random forest algorithm

Training data will then be entered into the random forest model and a final category will be assigned to each instance, based on a forest majority vote. Here, the example that is fed into every decision tree is described. The *Pt* function defines the predicted class probability using the instance v obtained over each tree and the P function shows that the projected class is based on a random forest (step 5). A higher likelihood determines the final category. Due to the random choice of the selected features and sampled data from the data set, each tree is separate, resulting in a slight variance (Step 9).

3.5 Location Extraction

Most tweets do not contain the location information because of the Twitter privacy policy. In these cases, we extract the location using meta-information from the user's profile and location information from the Twitter text.

4 Results and Discussions

In this section, the study presents the validation of proposed RF model with conventional classifiers in terms of various metrics that includes the following:

Accuracy is defined as the total true predictions for optimal functioning of the system and that provides the ratio of correct actionable tweets classified and total true actionable tweets.

where:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

TP - true positive actionable tweets
TN is the true negative actionable tweets
FP is the false positive actionable tweets
FN is the false negative actionable tweets

F-measure is the weighted harmonic mean of the recall and precision values, which ranges between zero and one. Higher the value of F-measure refers to higher classification performance.

F-measure is defined as the weighted mean of sensitivity and precision that defines the performance of a classifier and it is formulated as below.

$$F\text{-}measure = \frac{2TP}{2TP + FP + FN} \tag{2}$$

G-mean is an aggregation of specificity and sensitivity metrics that ensures an optimal balance between the variables in the datasets and it is defined as below:

$$G\text{-}mean = \sqrt{\frac{TP}{TP + FN} \times \frac{TN}{TN + FP}} \tag{3}$$

Mean Absolute Percentage error (MAPE) is the measure on actional tweet classification accuracy that finds total possible errors during the process of classification.

$$MAPE = \frac{100}{n} \sum_{t=1}^{n} \left| \frac{A_t - F_t}{A_t} \right| \tag{4}$$

where,

At - actual classes
Ft - predicted class
n - fitted points.

Sensitivity is the ability of the RF classifier to identify the true positive rate correctly.

$$Sensitivity = \frac{TP}{TP + FN} \tag{5}$$

The specificity defines the ability to correctly identify the true negative rate.

$$Specificity = \frac{TN}{TN + FP} \tag{6}$$

5 Datasets

The actionable tweets are classified from the input datasets namely Natural-Hazards-Twitter-Dataset. The dataset includes various hurricanes in United States that includes 2011 Tornado, Sandy (2012), Floods in 2013, Blizzard hurricane (2016), Matthew hurricane (2016), Hurricane (2017), Michael hurricane and Wildfires in 2018, Dorian hurricane in 2019. Further, the splitting of dataset undergoes training, testing and validation using RF classifier, where the results are given in Fig. 4 (Table 1).

Table 1. Datasets collected from various natural disasters

Dataset	Total Tweets
Tornado	3573
Sandy	2190
Floods	3597
Blizzard	3649
Matthew	5204
Hurricane	7823
Michael	4227
Wildfires	4596
Dorian	7140

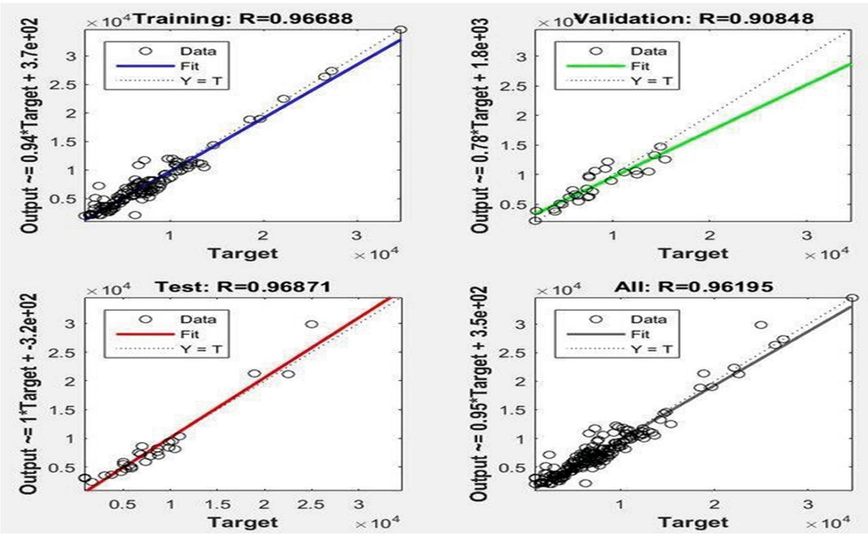

Fig. 4. Regression analysis on training/testing and validation

6 Experiment

The entire simulation is conducted in python environment and anaconda framework, where the classification of actionable tweets is carried out in a high end computing system that consists of CPU of AMD Threadripper 3970X 32-core, 120 GB SSD, 64 GB RAM on Windows 10, 64 bits.

7 Validation

Table 2. Comparison of accuracy between various models on different datasets

Dataset	KNN	NB	LR	SVM	ANN	**RF**
Tornado	55.87	56.17	58.26	58.52	59.88	**80.95**
Sandy	56.46	59.07	61.43	62.8	66.04	**82.89**
Floods	59.27	66.05	69.07	74.29	78.13	**85.17**
Blizzard	94.16	94.31	94.39	94.44	94.62	**94.96**
Matthew	96.1	96.12	96.13	96.22	96.24	**96.63**
Hurricane	96.65	97.37	97.4	97.48	97.49	**97.96**
Michael	97.56	97.56	97.64	97.64	97.66	**98.05**
Wildfires	97.63	97.63	97.71	97.71	97.73	**98.12**
Dorian	97.92	97.94	97.96	97.96	97.97	**98.31**

Table 2 shows the comparison of accuracy between various machine learning models including K-Nearest Neighbor (KNN), Naïve Bayes (NB), Support Vector Machine (SVM), Logistic Regression, Artificial Neural Network (ANN) and the proposed Glove-RF on different datasets. The results of simulation shows that the Glove-RF obtains improved accuracy on all datasets than other existing methods. The presence of Glove boost the RF to classify well the actionable instances than other methods.

Table 3. Comparison F-measure between various models on different datasets

Dataset	KNN	NB	LR	SVM	ANN	**RF**
Tornado	38.59	40.69	51.93	52.09	54.46	**62.93**
Sandy	52.57	60.24	60.58	61.04	62.57	**79.83**
Floods	58.45	66.99	67.88	69	74.04	**79.87**
Blizzard	66.94	69.92	70.25	70.49	75.05	**80.55**

(*continued*)

Table 3. (*continued*)

Dataset	KNN	NB	LR	SVM	ANN	**RF**
Matthew	69.88	70.14	70.31	73.13	76.36	**80.87**
Hurricane	77.58	77.71	78.23	79.31	79.99	**84.14**
Michael	86.08	86.2	88.14	88.17	89.53	**89.85**
Wildfires	86.14	86.26	88.2	88.23	89.59	**89.91**
Dorian	89.39	90.82	90.97	91.48	91.69	**92.65**

Table 3 shows the comparison of F-measure between various machine learning models including K-Nearest Neighbor (KNN), Naïve Bayes (NB), Support Vector Machine (SVM), Logistic Regression, Artificial Neural Network (ANN) and the proposed Glove-RF on different datasets. The results of simulation shows that the Glove-RF obtains increased F-measure on all datasets than other existing methods.

Table 4. Comparison G-mean between various models on different datasets

Dataset	KNN	NB	LR	SVM	ANN	**RF**
Tornado	43.71	56.63	59.66	44.91	74.92	**79.68**
Sandy	70.19	70.42	72.14	74.2	76.29	**81.93**
Floods	72.74	72.97	74.47	74.51	76.66	**82.46**
Blizzard	79.34	79.85	80.14	80.61	81.46	**86.07**
Matthew	79.63	79.87	80.38	81.14	81.72	**86.48**
Hurricane	82.08	82.93	84.55	86.11	91.15	**92.99**
Michael	93.46	94.22	94.59	94.66	94.99	**95.36**
Wildfires	94.22	94.29	94.66	94.73	95.06	**95.43**
Dorian	94.29	96.86	97.41	97.71	97.85	**98.19**

Table 4 shows the comparison of g-mean between various machine learning models including K-Nearest Neighbor (KNN), Naïve Bayes (NB), Support Vector Machine (SVM), Logistic Regression, Artificial Neural Network (ANN) and the proposed Glove-RF on different datasets. The results of simulation shows that the Glove-RF obtains increased g-mean on all datasets than other existing methods (Table 5).

Table 5 shows the comparison of MAPE between various machine learning models including K-Nearest Neighbor (KNN), Naïve Bayes (NB), Support Vector Machine (SVM), Logistic Regression, Artificial Neural Network (ANN) and the proposed Glove-RF on different datasets. The results of simulation shows that the Glove-RF obtains reduced MAPE on all datasets than other existing methods. This shows that the proposed method reduces the rate of classification errors than other methods.

Table 5. Comparison MAPE between various models on different datasets

Dataset	KNN	NB	LR	SVM	ANN	**RF**
Tornado	86.84	70.87	62.97	61.64	54.83	**15.62**
Sandy	71.05	70.82	62.92	61.59	54.28	**20.78**
Floods	71	64.67	57.95	39.83	54.24	**18.74**
Blizzard	68.31	30.99	30.47	28.86	36.97	**25.24**
Matthew	31.35	29.38	28.49	28.14	28.36	**18.14**
Hurricane	30.11	27.22	24.19	21.61	26.31	**25.58**
Michael	28.53	25.72	22.95	20.28	21.03	**21.28**
Wildfires	27.11	25.59	20.46	11.96	10.81	**16.38**
Dorian	19.58	16.91	16.82	9.48	10.63	**9.52**

Table 6. Comparison of sensitivity between various models on different datasets

Dataset	KNN	NB	LR	SVM	ANN	**RF**
Tornado	61.94	65.01	65.53	67.14	67.64	**68.2**
Sandy	64.65	65.45	67.51	67.87	69.69	**70.77**
Floods	65.89	66.62	72.07	73.84	74.04	**81.17**
Blizzard	68.89	70.29	73.06	75.74	85.19	**86.83**
Matthew	76.43	71.35	73.36	84.04	85.38	**89.1**
Hurricane	77.72	79.11	79.2	85.74	86.4	**92.79**
Michael	89.14	90.72	91.53	91.66	92.4	**92.86**
Wildfires	90.72	90.79	91.6	91.73	92.47	**96.78**
Dorian	90.79	95.77	96.87	97.45	97.73	**98.08**

Table 6 shows the comparison of sensitivity between various machine learning models including K-Nearest Neighbor (KNN), Naïve Bayes (NB), Support Vector Machine (SVM), Logistic Regression, Artificial Neural Network (ANN) and the proposed Glove-RF on different datasets. The results of simulation shows that the Glove-RF obtains increased sensitivity on all datasets than other existing methods. This shows that the Glove-RF identifies correctly the true positive rate than other methods.

Table 7 shows the comparison of specificity between various machine learning models including K-Nearest Neighbor (KNN), Naïve Bayes (NB), Support Vector Machine (SVM), Logistic Regression, Artificial Neural Network (ANN) and the proposed Glove-RF on different datasets. The results of simulation shows that the Glove-RF obtains increased specificity on all datasets than other existing methods. This shows that the Glove-RF identifies correctly the true negative rate than other methods.

Table 7. Comparison of specificity between various models on different datasets

Dataset	KNN	NB	LR	SVM	ANN	**RF**
Tornado	70.6	72.48	75.55	78.1	79.47	**80.58**
Sandy	73.59	74.57	77.41	80.57	82.09	**82.78**
Floods	74.38	76.47	78.08	80.78	82.57	**84.95**
Blizzard	94.91	94.97	95.01	95.66	95.7	**96.08**
Matthew	95.44	95.6	95.61	96.24	96.65	**97.34**
Hurricane	96.72	96.97	96.97	96.97	96.97	**97.95**
Michael	96.95	97.51	97.71	97.75	97.81	**98.18**
Wildfires	97.65	97.66	97.75	97.79	97.84	**98.21**
Dorian	97.72	97.73	97.82	97.82	97.91	**98.25**

The Glove-RF appears to indicate that the derived features generally do not boost the algorithms' performance with manual features (list of units, available related verbs, requirement related verbs, medical words, plural words and vocational words). This is something that is expected, because the addition of manual features is carried out to preserve the human expertise and intuition, and derived features depend heavily on data statistics. As a result, derived characteristics from a smaller dataset are likely to be noisy. However, the improvements in performance achieved in some 50% of cases indicate that the derived characteristics could be useful if there was a bigger dataset.

Despite its advantages, the study provides certain limitations that includes lacks of models on cleaning, crawling, storing the twitter data, consideration of social and visual features in acquiring robust classification after the application of machine learning hybrid model for classifying the multi- class labels.

8 Conclusions

In this study, RF effectively classifies the actionable tweets to accurately identify the disaster location and required help in disaster zone. The model involves collection of tweets, pre-processing, classification and the extraction the information including the determination of location. GLoVe word representation with pre-trained word vectors enables the RF classifiers to perform well in classifying the actionable tweets. This helps in the determination of location and enables optimal classification of actionable tweets. This model thus helps in classifying the tweets posted by the users on twitter.org. The classification of actionable and non-actionable classes via RF classifiers shows increased accuracy, sensitivity, specificity and reduced MAPE than conventional machine learning models. In future, the inclusion of features related to context can be utilized to increase the system performance.

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