Natural Language Processing with Disaster tweets using Bidirectional LSTM

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Abstract- **The growth and impact of social network resulted not only in huge collection of data but also as a reliable source of data to draw valuable information from. Twitter, one of the major social platforms is used for collection of tweets related to a disaster. The tweets are written by the people in an area who are affected by a particular disaster for multiple reasons: to seek help, to express grief or to show the seriousness of the situation. Some tweets are also written by the non-local people to bring awareness. These tweets are identified by the hashtags and collected for further analysis and classification of tweets as original or hoax. The method discussed in this paper is bidirectional long short-term memory to classify tweets and obtain accuracy of 88 percent.**

Keywords – Disaster, GloVe, Long Short Term Memory (LSTM), Natural Language Processing, Tweets

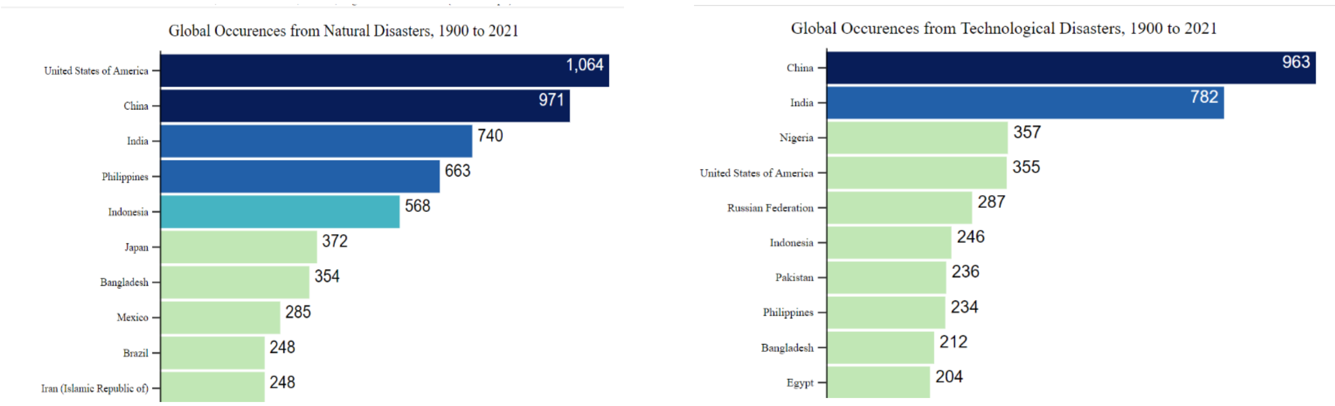
I. Introduction

The seriousness of the situation is sometimes not understood and it leads to negligence which results in grave consequences if immediate actions are no undertaken by the officials. Every disaster may not be covered by mass communication media immediately. The recent tragedies like Vizag gas leak, is a striking example. Social media will help in this situation in a better and faster way than the mass media. So, many researches are conducted to check the validity of the data available on social media. Social media is a source of plethora of information and if used properly it helps in the betterment of society.

EM-DAT is an online largest repository of disaster data collection related to the disasters across the world. These disasters are divided into two categories: natural and technological disasters (figure 1). The data collected from 1990-2021 shows the number of disasters in various countries and it is evident that India stands in the top second and third positions for technological and natural disasters respectively. So, it becomes crucial to tackle situations immediately without any delay. So, a robust and accurate model built helps to identify the fake tweets from real tweets.

Figure 1

Image source: EMDAT



One of the most important application of natural language processing is to analyze technological disasters like oil or gas leakage, man-made accidents, software hacks or collapses and many more. Since, impromptu action is necessary to be taken during these disasters that can cost lives, it is necessary to use high performance models.
The following table shows the efficiency of disaster management using twitter data analysis.(Figure 2)

Table 1. Characteristics of studies about disasters and Twitter.

No.	Disaster	Finding	Disaster Phase	Country	Ref.
1	Typhoon	People and organizations have used Twitter more often to retweet second-hand information/social networking users in Philippines are more likely to pay attention to news released in traditional media than social media.	response	Philippines	(Takahashi et al. 2015)
2	Earthquake, Tsunami	The results suggest that Twitter can be used to track and measure the public's mood after disasters.	Response, Recovery	Japan	(Doan et al. 2011)
3	Wildfire	The geographic awareness of people is strong about critical events and people are interested in tweeting about fire damage, firefighting and thanking firefighters/official tweets play a key role in the firefighting network.	Preparedness, Response	USA	(Wang et al. 2016)
4	Earthquake	Rumors about earthquakes spread more than anything else on Twitter.	Response	Chile	(Mendoza et al. 2010)
5	Earthquake	Twitter was used as a tool to report on the situation by the affected people. This article suggests that Twitter can be used as a tool for rapid assessment of an accident, as well as for the publication of accurate information by officials.	Response	Japan	(Acar and Muraki 2011)
6	Earthquake	Twitter is useful as a tool to show people's mental health, especially in the early days of a disaster.	Response	Japan	(Cho et al. 2013)
7	Earthquake	During an earthquake, organizations used Twitter as a tool for risk communication, to collect public donations and to provide psychological support.	Response, Recovery	Haiti	(Gurman and Ellenberger 2015)
8	Earthquake	Twitter was used for disaster assessment, response monitoring and to help the affected people.	Response	Haiti	(Smith 2010)
9	Storm	A lot of first-hand information was published about the current situation. Twitter is useful for disaster assessment.	Response	USA	(Mukkamala and Beck 2016)
10	Tornado	People trusted personal accounts more than governmental accounts to find out about a tornado. Influential people play a big role in providing the right information. Using the right hashtag will	Response	USA	(Cooper et al. 2015)

Figure 2 Importance of twitter Data Analysis

II. Methods and proposed system

2.1

The proposed model is trained and tested on the dataset created by the company figure-eight and originally shared on their website 'Data for everyone'. The dataset consists of 10,878 tweets divided into train data (7614) and test data (3264). Considering dataset with text(string) and id(int) and the following steps are followed. These, steps are performed on train and test data set.

2.2

The tweets are extracted by crawling through certain hashtags varying across different regions, demographics and disasters. These highly diverse tweets are taken and cleaned before analyzing.
a) Stripping the strings and remove the duplicates present.
b) Duplicates are the text which have same text and target, they might result in false metrics.
c) Removing URL's if present any with the help of regular expressions by substituting them with null strings. URL's and html tags are not sources of valuable information and are thus ignored. (Figure 3)

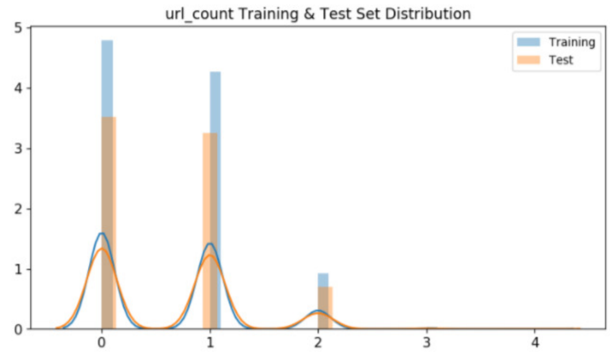


Figure 3

d) Removing the stop words, punctuation marks.
Stop words are the most common words in any natural language. For the purpose of analyzing text data and building NLP models, these stop words might not add much value. For example; for, when, and, the etc. Punctuation marks are removed from the text (figure 4 a) These include ('#', '.', ',', '/','?') shown in figure 4 b.

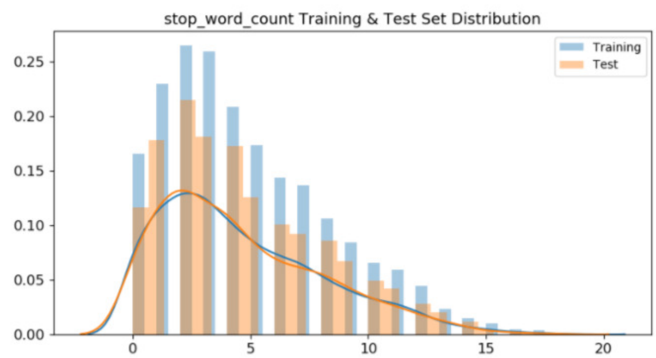


Figure 4a

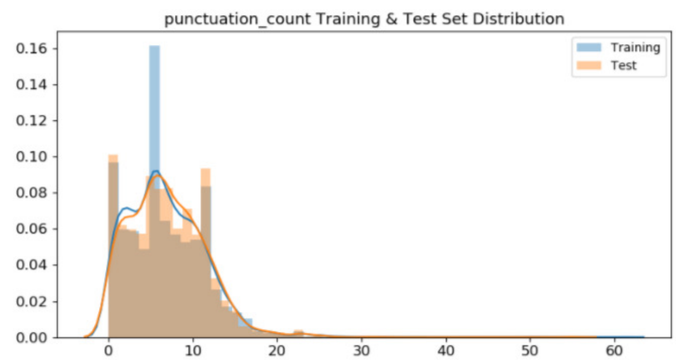


Figure 4b

e) Performing stemming
Stemming: It is the process of reducing a word to its word stem that affixes to suffixes and prefixes or to the roots of words known as a lemma. For example; advantageous to advantage; determination to determine.

5)Tokenization: Tokenization is splitting of the text or sentence into smaller parts called as tokens. The text with less than two tokens are removed as they do not contribute for the prediction. (Figure 5)

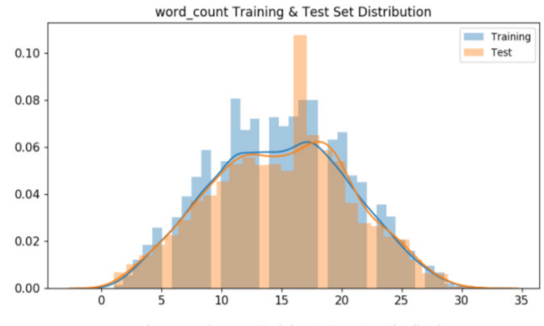


Figure 5

2.3

Word embedding methods learn a real-valued vector representation for a predefined fixed sized vocabulary from a corpus of text. The Global Vectors for Word Representation, or GloVe, algorithm is an extension to the word2vec method for efficiently learning word vectors, developed by Pennington, et al. at Stanford. GloVe is an unsupervised learning algorithm for obtaining vector representations for words. [9].The output vector obtained by using GloVe is used as input to the bi-lstm model.

2.4

Building a Bi-LSTM network.

Bidirectional LSTM: Bidirectional recurrent neural networks (RNN) are really just putting two independent RNNs together. This structure allows the networks to have both backward and forward information about the sequence at every time step [1,2,3]

Bidirectional LSTM is used as it runs inputs in two ways, one from past to future and one from future to past and what differs this approach from unidirectional is that the Bi- LSTM that runs backward preserves information from the future and using the two hidden states combined you are able in any point in time to preserve information from both past and future.

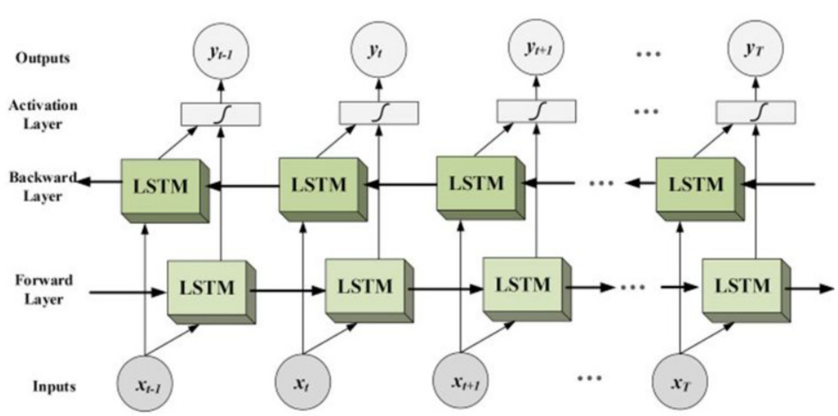


Figure 6

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The proposed model consists of three bidirectional lstm layers with dropout of 0.2. The next two layers are densely connected layers with drop out of 0.1 and operate using “ReLu” activator functions. The last layer used sigmoid function to predict binary output. For clear understanding of the input and output of each layer please refer below figure 7.

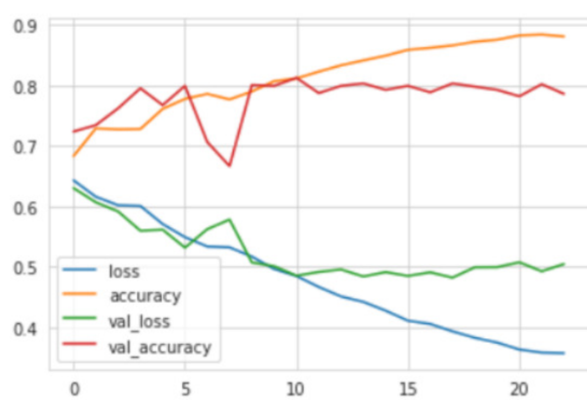
```
Model: "sequential_3"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
bidirectional_6 (Bidirection (None, 20, 128)           186880
_________________________________________________________________
dropout_6 (Dropout)          (None, 20, 128)           0
_________________________________________________________________
bidirectional_7 (Bidirection (None, 20, 128)           98816
_________________________________________________________________
dropout_7 (Dropout)          (None, 20, 128)           0
_________________________________________________________________
bidirectional_8 (Bidirection (None, 128)               98816
_________________________________________________________________
dropout_8 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_6 (Dense)              (None, 64)                8256
_________________________________________________________________
dense_7 (Dense)              (None, 64)                4160
_________________________________________________________________
activation_2 (Activation)    (None, 64)                0
_________________________________________________________________
dense_8 (Dense)              (None, 1)                 65
=================================================================
Total params: 396,993
Trainable params: 396,993
Non-trainable params: 0
```

Figure 7

2.5 Training data and Results

The training data is divided into batches of 64. The optimizer used is Adam optimizer. The data is trained for 100 epochs. The loss is binary cross entropy loss and metric optimized is accuracy. At end of the training data, the accuracy is found out to be 87.2 percent and loss is found out to be 30 percent approximately. The model obtained an accuracy of 85.6 percent on test data (Figure 8). This is comparatively higher than traditional machine learning algorithms like naive bayes and support vector machine. Therefore, bidirectional lstm works with an increased accuracy as compared to other algorithms.

Figure 8



IV.CONCLUSION

Bidirectional LSTM has always been proved to work far better than other neural network algorithms for text analysis or sentiment analysis by running in both the directions effectively. Therefore, it is necessary to encourage the citizens to provide useful information in social media with proper hashtags. The qualitative and quantitative analysis together can help the officials to better understand the urgency. So, this system works better than earlier used mass-media communication for disaster management. NGO's and other social organizations can also use this method for faster identification and take necessary action.

The proposed works better than the traditional machine learning classification algorithms and thus with higher accuracy for identification and quick response to the tweets related to a disaster. The model can be used together for sentiment analysis as well as the results of both can be combined to build a hybrid model with further accuracy. Therefore, the scope for research in the future for this problem is huge and is beneficial.

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