Classification of Disastrous Tweets on Twitter using BERT Model

**Mr. M. Purna ChandraRao[1], Chebrolu Taraka Ramarao[2], Nalleboyina Dinesh Babu[3]
Pilli Lokesh[4], Unnava Dattathreya[5]**

[1]Associate Professor, Department of Information Technology, KKR & KSR Institute of Technology and Sciences(A), Guntur, India.
[2,3,4,5]Undergraduate Students, Department of Information Technology, KKR & KSR Institute of Technology and Sciences(A), Guntur, India.

---***---

Abstract - *With today's technology, each person's online presence opens the door to a massive informational vast collection that can be used for a broad variety of applications, ranging from analyzing market trends to understanding the general emotional state of the population. Text and sentiment analysis is now lot simpler than it was a few years ago because to advances in technology and NLP approaches. Each Tweet's label reflects a variety of disasterrelated data that could be used in many ways during an emergency response. When someone tweets a warning about a crisis or impending tragedy and our BERT models immediately identify this, we are able to respond as quickly as possible, which helps to save lives. BERT is a free machine learning framework for handling natural language (NLP). Our project's primary goal is to determine whether or not a tweet refers to a genuine disaster.*

***Key Words*:** Tweets, Bidirectional Encoder Representations from Transformers (BERT), NLP, Disaster

1. INTRODUCTION

The traditional method of classifying texts usually uses Logistic Regression, Support Vector Machine, Naive Bayes, Gradient Boosting, and other basic machine learning models. In order to feed text sequences into classifiers, which may experience the issue of typing error and produce noisy words for the corpus, these methods require pre - processing and feature engineering processes to encode text sequences in vector form.

The method for compressing text into vector forms affects how well the model performs. In this case, comprehending word context is crucial for analyzing a tweet's intention. A tweet like this can be an example: "She claims that no one is to blame for her disease. It was merely a natural accident. Despite the term "accident" being included, it does not refer to any danger or emergency but rather describes a typical discourse. Let's say that a similar tweet would read, "He had a workplace accident, I was hurt." In this context, "accident" refers to a catastrophe, and the tweet is describing an emergency. The two examples demonstrate how a single word can have several meanings depending on its context. Therefore, it's critical to comprehend word context in order to evaluate the attitude and aim of a tweet.

Various researchers suggested various approaches of deciphering a word's meaning.

Using neural network-based techniques, such as Skip-gram and Fast Text, it is possible to learn word embeddings from enormous word corpora, which is useful for completing many NLP tasks. These techniques are also employed for Twitter data sentiment analysis. The static embedding offered by such embedding learning techniques, however, only applies to a single word in a document. As a result, in the two examples given above for these techniques, the definition of the word "accident" would remain the same.

1.1 Background of Study

During any emergency situation, Twitter or Facebook serve as a platform for information dissemination. Location, user, incident type, personal harm, and infrastructure damage are all included in this data. The information indicates that the crisis is under control and For rescue operations, damage and location estimation is done. However, it is tough to rescue because of the speed and volume of information that come at one, making it harder to distinguish vital information from irrelevant. Our model aims to automatically extract important information and classifications.

1.2 Purpose of Study

The amount of time available to protect people during an incident is limited. Therefore, the rescue/protection effort should be launched as soon as feasible. Twitter is now a significant communication tool platform. By disseminating the information or word of the damage, it greatly aided. It became more difficult for communities affected by disasters and rescue teams to act promptly since it was harder to distinguish significant ones from irrelevant ones. Our BERT technology, which aids in deciphering the meaning of ambiguous language in text, can rapidly identify tweets regarding emergencies or looming disasters. This would be able to respond more quickly than usual, saving lives.

1.3 Elaboration of Study

Recognizing pertinent posts on the social network, in this case Twitter, is the main goal. Recent advancements in the field of NLP have had an impact with common techniques for this particular type of challenge.

Recent research has revealed that deep learning is among the finest techniques for managing natural language.

For deep learning, the supervised training procedure using a lot of data produces strong results. A deep learning model called BERT (Bidirectional Encoder Representations from Transformers) was created by Google. Since Google made it available, the majority of us have accepted it and used it for a variety of text classification jobs. One of the most recent NLP development milestones, the release of BERT marked the start of a new phase in the field.

2. RELATED WORK

Social networking sites like Facebook and Twitter have been extremely popular in recent years as a means of online communication that generates massive amounts of data. Additionally, during disasters, people post enormous amounts of timely and relevant information on these platforms, which is beneficial to the charitable organisations for disaster relief efforts. However, it is not simple to chance upon and identify tweets and postings that are connected to a current event. For the purpose of finding tweets linked to the disaster, many different methods have been devised. Some of these methods have relied on conventional machine literacy techniques, but more recently, Deep Learning techniques have been advocated as efficient means to categorise tweets in emergency situations. Here is a quick rundown of the popular models. Do not use abbreviations in the title or heads unless they are unavoidable.

Regarding conventional methods, Avvenuti et al. have created a social media-based system for earthquake discovery that is based on tweets and Twitter replies. To cut down on irrelevant material, characteristics like URLs, citations, words, characters, punctuation, and shoptalk and derogatory language are also utilised in bracket stages. They eventually developed a temporal analysis burst finding method that counts the amount of communications within a time window. While the authors in used Support Vector Machine (SVM) as a classifier to first filter irrelevant tweets before mining Twitter data for real-time earthquake detection. Then, a probabilistic model that incorporates the toxic process is created for temporal analysis in order to determine the time at which the earthquake occurred.

Recently, some methods have successfully classified tweets during a catastrophe event using deep learning techniques. As an example, Caragea et al. have suggested an Convolutional Neural Networks-based methodology is used to find instructive messages in social media aqueducts during crisis occurrences. On numerous datasets of dispatches from flooding events, this strategy has been demonstrated to significantly outperform models that employ the "bag of words" and n-grams as features. Text mining utilising Natural language processing has produced a number of noteworthy and laudable research achievements.

3. LITERATURE REVIEW

[1] The authors Hamid Bagheri and Md Johirul Islam had developed much predictive model for sentiment analysis of twitter (Bagheri H , Islam Md J, 2017) . They used Textblob python library for text processing and NLTK for Natural language Processing. They classified tweets based on movies, politics, fashion, fake news, justice and humanity into 3 categories of tweets – positive, neutral and negative.

[2] The authors Ali Hasan, Sana Moin, Ahmad Karim, and Shahaboddin Shamshirband had collected tweets pertaining to certain political topics and hastags originating in Pakistan and did sentiment analysis of the tweets using Naive Bayes and SVM classifier (Hasan A , Moin S, Karim A , Shamshirband S , 2018) . They used Textblob , SentiWordNet and WWSD for text analysis and did a comparison after classifying the tweets into positive , neutral and negative categories.

[3] The authors Aurangzeb Khan, Baharum Baharudin, Lam Hong Lee, Khairullah Khan had worked in the field on text mining of NLP using feature extraction (tokenization , stop-words removal , stemming) ,feature selection (document vector representation) and did a comparative study of text classification using SVM , Naive Bayes and KNN (Khan A , Baharudin B, Lee L H, Khan K , 2010) .

[4] Jermaine Marshall , Dong Wang Authors showed that Mood-Sensitive Truth Discovery For Reliable Recommendation Systems in Social Sensing. This work is motivated by the need to provide reliable information recommendation to users in social sensing. Social sensing has become an emerging application paradigm that uses humans as sensors to observe and report events in the physical world.

4. SOFTWARE REQUIREMENT SPECIFICATIONS

4.1 Functional Requirements

A functional requirement specifies how a system or one of its components should function. A function is defined as a collection of inputs, behaviors, and outputs. It also relies on the kind of system that uses the programme, the anticipated users, and the kind of software.

4.1.1 Software Requirements

- Windows7
- Numpy
- Keras
- Seaborn
- TensorfFlow
- Google Collab

Google Collab:

Google Collab was created to give anyone who requires access to GPUs and TPUs for building a machine learning or deep learning model free access to them. A more advanced version of Jupyter Notebook is Google Collab. The interesting capabilities that each contemporary IDE offers are abundant in Google Collab, in addition to many others. Below is a list of some of the more fascinating aspects.

Features of Google Collab:

- Interactive tutorials for learning neural networks and machine learning.
- Create and run Python 3 programs without a local setup.
- Use the Notebook to run terminal commands.
- Import data from outside resources like Kaggle.
- Your notebooks should be saved to Google Drive.
- No-cost cloud computing, GPUs, and TPUs.
- Integrate with Tensor Flow, PyTorch, and Open CV.
- Directly import or publish to/from GitHub.

4.1.2 Hardware Requirements

- Processor -i3
- Memory -2GB RAM

4.2 Non-Functional Requirements

A non-functional requirement is one that specifies criteria rather than specific behaviours that can be used to evaluate how well a system operates.

The following are qualities of a system, sometimes known as non-functional requirements:

- Legal or Regulatory: Which industry's regulations must a product abide by?
- Performance: Examine how well the product responds to user activity.
- Usability: The product is simple to use.
- The application ought to run on any platform.
- It's important to preserve consistency.
- It needs to consistently anticipate the same outcome for similar data.

5. PROPOSED SYSTEM

Bidirectional Encoder Representations from Transformers (BERT), a model that we have suggested, gives embeddings of a word based on its context terms. When performing various NLP tasks including entity recognition, text classification, and text summarization. Traditional embedding learning techniques were outperformed by the BERT model. However, it is intriguing to learn how contextual embeddings could aid in comprehension of literature relating to disasters. Due to this, we intend to examine the catastrophe prediction job utilizing Twitter data in this study using both context-free and contextual embeddings. For the prediction job, where the word embeddings are usually used as input to the models, we apply several conventional machine learning techniques and neural network models. Contextual embeddings perform better, as we demonstrate.

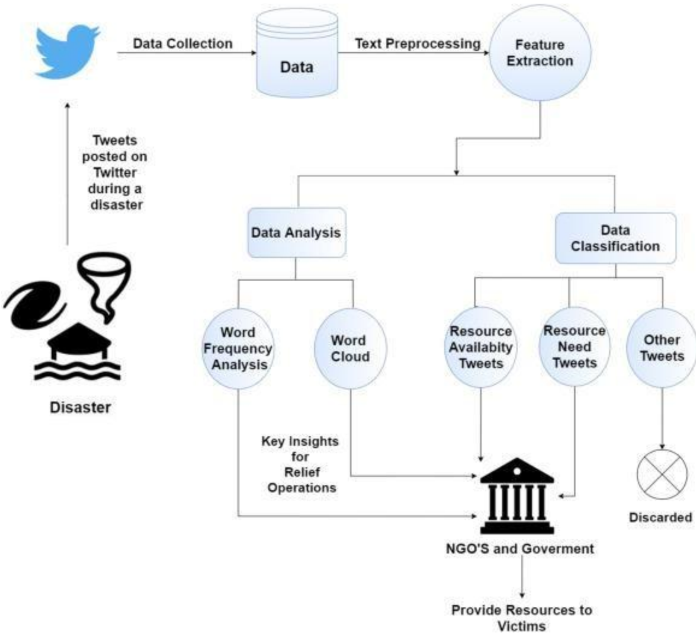

Fig: disaster tweets classification

Bidirectional Encoder Representations from Transformers (BERT)

Google AI Language researchers published a document titled BERT (Bidirectional Encoder Representations from Transformers) in their journal. It is an advanced Transformer.

Coding stack. The Book Corpus dataset and Wikipedia are used to train it. By presenting cutting-edge research in a variety of NLP techniques, such as Question Answering Natural Language Inference (MNLI), it sparked interest in the machine learning community. It makes use of Transformer, an attention mechanism that understands how words in a sentence relate to one another in context. Transformer's original design supports the following mechanisms: a decoder that produces a mission predictor and an encoder that receives text input. Only the encoder technique is needed because BERT's goal is to construct a language model.

DATA SET

	id	keyword	location	text	target
0	1	NaN	NaN	Our Deeds are the Reason of this #earthquake May ALLAH Forgive us all	1
1	4	NaN	NaN	Forest fire near La Ronge Sask. Canada	1
2	5	NaN	NaN	All residents asked to 'shelter in place' are being notified by officers. No other evacuation or shelter in place orders are expected	1
3	6	NaN	NaN	13,000 people receive #wildfires evacuation orders in California	1
4	7	NaN	NaN	Just got sent this photo from Ruby #Alaska as smoke from #wildfires pours into a school	1
5	8	NaN	NaN	#RockyFire Update => California Hwy. 20 closed in both directions due to Lake County fire - #CAfire #wildfires	1
6	10	NaN	NaN	#flood #disaster Heavy rain causes flash flooding of streets in Manitou, Colorado Springs areas	1
7	13	NaN	NaN	I'm on top of the hill and I can see a fire in the woods...	1
8	14	NaN	NaN	There's an emergency evacuation happening now in the building across the street	1
9	15	NaN	NaN	I'm afraid that the tornado is coming to our area...	1

Fig: Dataset

We used the Kaggle dataset for this study. "https://raw.githubusercontent.com/laxmimerit/twitterdisaster-predictiondataset/master/train.csv" allowed users to download the dataset. We evaluate if a particular tweet specifically mentions a disaster based on its 10873 comments. 57.03% of the 10,873 data points were made up of tweets about disasters, leaving the remaining data. The dataset we utilized includes the information listed below.

- Id (tweet identification),
- text (the content of the tweet),
- location: location the tweet was sent from
- keyword: A relevant keyword in the tweet
- target: Output that tells if a tweet is a real disaster (1) or not (0)

STEPS INVOLVED

- Data Collection
- Data Preprocessing
- Data Visualization

6. ALGORITHMS USED

BERT:

BERT, which stands for Bidirectional Encoder Representations from Transformers, is based on Transformers, a deep learning model in which every output element is connected to every input element, and the weightings between them are dynamically calculated based upon their connection. (In NLP, this process is called attention.) Historically, language models could only read text input sequentially -- either left-to-right or right-to-left -- but couldn't do both at the same time. BERT is different because it is designed to read in both directions at once. This capability, enabled by the introduction of Transformers, is known as bidirectionality. Using this bidirectional capability, BERT is pre-trained on two different, but related, NLP tasks: Masked Language Modeling and Next Sentence Prediction.

SVM (SUPPORT VECTOR MACHINE):

Support Vector Machine (SVM) is a supervised machine learning algorithm used for both classification and regression. Though we say regression problems as well its best suited for classification. The objective of SVM algorithm is to find a hyperplane in an N-dimensional space that distinctly classifies the data points.

TF-IDF:

TF-IDF TF-IDF stands for "Term Frequency — Inverse Document Frequency". This is a technique to quantify words in a set of documents. We generally compute a score for each word to signify its importance in the document and corpus. This method is a widely used technique in Information Retrieval and Text Mining.

7. RESULTS

Data Set	Number of Tweets	_Number of targeted tweets	Number of non targeted tweets
Data Set 1	7613	3271	4342
Data Set 2	11370	2114	9256

We use two separate data sets with varied counts for this project, train our models on both sets of data, and then evaluate the outcomes. In the data set, there are 7613 tweets, of which 43% are about disasters and the rest are not. In data set 2, there are 11370 tweets, or a fairly big amount, of which 18.5% are about disasters. On both data sets, our BERT model performs more accurately.

Accuracy of Different models for different data sets:

Model	*Data Set*	*Accuracy*
Classification with TF_IDF and SVM	Data Set 1	0.80
	Data Set 2	0.901
Classification with Word2IDFVC and SVM	Data Set 1	0.57
	Data Set 2	0.813
Bert Model	Data Set 1	0.869
	Data Set 2	0.9167

We can infer from this table that the BERT model has more accuracy than the other two models for both data sets. For dataset 1, the accuracy of TF IDF and SVM is.80, and when we train and test the model using further data sets, the accuracy rises as a result of the additional data sets. Due to the second model's use of less data than the first, we see that dataset 2's accuracy is higher than dataset 1's. Last but not least, our BERT model has a maximum accuracy of.9167 and great accuracy in both datasets.

8. CONCLUSION

This project's goal was to develop a BERT language model-based method for determining if a tweet is a disaster or not. It was set up as a two-step pipeline, with the first step entail pre-processing steps to convert Twitter lingo, including emojis and emoticons, into plain text, and the second step utilizing a version of BERT that was pre-trained on plain text to fine-tune and classify the tweets with respect to their polarity. Pretrained language models are widely available in many languages, avoiding the time-consuming and resource-intensive model training directly on tweets from scratch, allowing to focus only on their finetuning; available plain text corpora are larger than tweet-only ones, allowing for better precision in the prediction of language usage. In order to further determine its applicability and generalizability, the suggested approach will also be tested and evaluated in relation to additional datasets, languages, and social media sources, such as Facebook postings.

9. REFERENCES

[1] Becken, S.; Stantic, B.; Chen, J.; Alaei, A.R.; Connolly, R.M. Monitoring the environment and human sentiment on the Great Barrier Reef: assessing the potential of collective sensing. J. Environ. Manag. 2017, 203, 87–97. [CrossRef] [PubMed].

[2] Takeshi Sakaki, Makoto Okazaki, and Yutaka Matsuo. Earthquake shakes twitter users: real-time event detection by social sensors. In Proceedings of the 19th international conference on World wide web, pages 851–860. ACM, 2010.

[3] Devlin J, Chang M. W, Lee K, and Toutanova K BERT: Pretraining of deep bidirectional transformers for language understanding 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies - Proceedings of the Conference.

[4] Hasan A , Moin S, Karim A , Shamshirband S (2018). Machine learningbased sentiment analysis for twitter accounts. Mathematical and Computational Applications, 23(11), 1-15.

[5] Bagheri H , Islam Md J (2017). Sentiment analysis of twitter data. Computer Science Department Iowa State University, United States of America.

[6] https://towardsdatascience.com/bert-explainedstate-of-the-art-language-model-fornlp%02f8b21a9b627

[7] https://towardsdatascience.com/workflow-of-amachine-learning-project-ec1dba419b94

[8] https://www.kaggle.com/c/twitter-sentimentanalysis2

[9] https://towardsdatascience.com/tf-idf-for-documentranking-from-scratch-in-python-on-real-worlddataset-796d339a4089

[10] https://www.tutorialspoint.com/google_colab/what_is_google_colab.htm

[11] https://www.applause.com/blog/functional-testingtypes-examples