Disaster Tweet Classification using Natural Language Processing & Deep Learning

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Abstract - Classifying tweets about disasters is crucial for effective disaster management and response. This paper offers a thorough examination of tweet classification methods especially using NLP with an emphasis on tweets relevant to disasters. Deep learning models, machine learning algorithms, and keyword-based filtering are some of the techniques that are out there. The outcomes show how well deep learning models - in particular, RNNs and CNNs - classify tweets about disasters. We used CNN, RNN, Bi-RNN, RoBERTa and GLU for tweet classification. Finally, we will compare the accuracies of these different methods and pick the best out of them. These results aid in the creation of reliable tweet classification systems for quick and efficient disaster relief operations.

Keywords - Convolutional neural networks(CNN), recurrent neural networks (RNN), Bidirectional Recurrent Neural Network (Bi-RNN), Robustly Optimized Bidirectional Encoder Representations from Transformers Approach (RoBERTa) (Transformer Model), Gated Linear Unit(GLU).

I. INTRODUCTION

In the era of social media, the rapid dissemination of information during disasters can be a challenge. Natural language processing (NLP) techniques offer powerful tools to shift through the vast amounts of data generated on platforms like Twitter (X) to identify critical information during emergencies. This paper delves into the classification of disaster-related tweets, aiming to distinguish between disaster tweets that are real or not

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With the increasing prevalence of social media usage during crises, the ability to automatically classify tweets as disaster or not holds significant importance for emergency response teams, journalists and researchers. By leveraging DL methods that are based on text classification algorithms, this paper seeks to contribute to the development of effective tools for identifying and prioritizing relevant information in real time.

The challenges in disaster tweet classification lie in the ambiguity and brevity of tweets, as well as the need to distinguish between actual disaster related content and noise or misinformation. To address these challenges, this paper uses RoBERTa (Transformer Model), CNN, RNN, Bi-RNN to get more accuracy in the results.

Ultimately, the classification of disaster tweets not only aids in real time situational awareness but also supports efforts in disaster management, resource allocation and public safety. This paper aims to advance the field of NLP for disaster response by providing insights and methodologies for effectively classifying tweets during emergencies.

II. RELATED WORKS

A. “Classification of Disaster Tweets using Machine Learning and Deep Learning Techniques”

Asinthara K et al. [1] Using machine learning and deep learning approaches, the authors conducted an informative analysis of disaster tweets. The goal of the project is to improve situational awareness in times of disaster by utilizing sentiment analysis. Tweets are pre-processed and structured using Natural Language Processing (NLP) techniques, which allows tweets to be categorized into several categories of disasters. Effective classifiers for tweet classification are created using supervised learning approaches such as the Naïve Bayes Classifier algorithm and Support Vector Machine. Additionally, adding an emoticon detection method to the classification process improves it and gives clear explanations. The results of this study have important ramifications for news organizations and disaster relief groups, providing them with important information to better comprehend the dynamics of disasters and take required actions.

B. “Classifying Natural Disaster Tweet using a Convolutional Neural Network and BERT Embedding”

Lucas Satria Aji Dharma and Edi Winarko [2] This study uses convolutional neural network (CNN) models to handle the problem of differentiating tweets relating to disasters from tweets unrelated to disasters during natural calamities. As Twitter becomes a more widely used microblogging site, there is a noticeable increase in the amount of tweets about different occurrences, such as natural catastrophes. Still, not every tweet about a calamity offers useful information about the incident. Consequently, in order to distinguish between tweets about disasters and those about non-disasters during such situations, the research suggests a classification scheme. The suggested approach compares with Word2Vec, another embedding technique, and makes use of a Convolutional Neural Network (CNN) with Bidirectional Encoder Representation from Transformers (BERT) embeddings. A high level of accuracy (97.16%), precision (97.63%), recall (96.64%), and f1-score (97.13%) is achieved by the CNN model with BERT embeddings for tweet classification, according to evaluation results. This shows how effective the proposed approach is at accurately identifying tweets related to disasters among the noise of non-disaster tweets during natural disasters.

C. "Predicting Disaster Tweets using Enhanced BERT Model"

Premkumar Duraisamy et al. [3] This study explores Twitter's importance as a crucial means of communication in emergency scenarios. People can quickly report situations they encounter thanks to the widespread use of cellphones, which makes Twitter a key channel for sharing information in real time. As a result, many organizations are becoming more and more interested in automatically watching Twitter in order to obtain vital information during emergencies. Social media sites such as Twitter provide a common place for people to share concerns related to their area, activities, and personal experiences, which can yield insightful information. Numerous rescue organizations keep a close eye on these kinds of data in order to minimize casualties and quickly discover crises. However, it is very hard for humans to manually sort through massive amounts of data in order to identify dangers in real-time. Previous research has suggested using machine learning approaches to analyze text sentiment and encoding words in a format that is computationally comprehensible in order to address this difficulty. The development of Advanced Contextual Embeddings, like Bidirectional Encoder Representations from Transformers (BERT), has completely changed the way that word representations from a particular document are produced. Previously, these methods only supplied single embeddings. While there isn't much research on the use of BERT embeddings in twitter analysis linked to disasters, these representations have proven successful in a number of Natural Language Processing (NLP) tasks, suggesting that they could be useful in tweet analysis connected to disasters.

D. "Natural Language Processing for Prediction of Disaster Tweets using Ensemble Learning"

Mohit Chowdhary and Poonam Nandal [4] This study investigates how social media, in particular Twitter, might be a useful information source for characterizing and forecasting occurrences, particularly those that are connected to natural disasters. As a result of increased digitalization and the widespread use of social media, it is now clear that social events propagate quickly and that human connectedness has increased. This rapid and widespread information distribution offers social scientists and computer scientists a great opportunity. Posts on social media can be categorized according to the emotions they express because these posts frequently include emotional clues. Techniques based on Natural Language Processing (NLP) provide a way to efficiently complete this classification procedure. The authors of the article assess tweets that contain phrases related to disasters using an ensemble learning technique. For this, a variety of preprocessing methods as well as the TF-IDF (Term Frequency-Inverse Document Frequency) feature extraction methodology are used. Furthermore, using metrics like f1 score, accuracy, precision, and recall, the authors compare the performance of multiple classification methods, such as Gaussian Naive Bayes, Random Forest, and Logistic Regression. The purpose of this study is to provide light on how social media data can be used effectively for event description and prediction, especially in the case of catastrophic events.

E. "Social Media Analytics for Disaster Management using BERT Model"

Sherin R Varghese et al. [5] In this study the necessity for efficient disaster management systems has been brought to light by the rising frequency and severity of both natural and man-made disasters. Social media platforms, especially Twitter, have grown exponentially in the last ten years, revolutionizing public mood research, information distribution, and real-time communication during such emergencies. As a result, there is a rising need for disaster management systems based on social media that can make good use of this abundance of data. In order to meet this demand, this research project introduces a sentiment analysis framework that is specifically designed for use with Twitter data. Its fundamental component is BERT (Bidirectional Encoder Representations from Transformers). Furthermore, a variety of Natural Language Processing (NLP) techniques are used for comparison and assessment. The results of this investigation show that the addition of BERT leads to a notable improvement in accuracy, outperforming competing models by a margin of 5% to 7%. As a result, this study highlights how well BERT based sentiment analysis may be used to optimize disaster management plans, providing insightful information for efforts to mitigate and respond to disasters.

F. "A Detailed Analysis on Disaster Tweet Analysis Using Deep Learning Techniques: DTWEET"

Ajit Kumar and Somashekhara Reddy [6] This study emphasizes how important social media platforms, especially Twitter, are becoming as routes for communication when there is a crisis. Since Personal Digital Assistants (PDAs) are so widely used, people may quickly communicate information on ongoing crises. Although public frameworks for disaster response have been established by states and crisis management organizations, the effectiveness of these measures ultimately rests on the opinions of individuals impacted. People regularly share updates on online platforms during and after a crisis, adding to the massive amounts of unstructured data. Text mining and artificial intelligence (AI) algorithms are used to find tweets that contain disaster-related keywords and phrases in order to efficiently filter this data. The goal of this work is to differentiate between real and fraudulent tweets about disasters using Natural Language Processing (NLP) techniques and classification models. The dataset includes tweets about real disasters as well as those about made-up disasters. It was downloaded from the Kaggle website. In order to support crisis response and management initiatives, the authors hope to create a trustworthy technique for differentiating between authentic and fraudulent disaster-related content on Twitter through their research.

G. "A Deep Learning Approach to Outbreak related Tweet Detection"

B. A. S. S. B. Jayawardhana and R. A. C. P. Rajapakse [7] This study addresses the growing importance of social media platforms as channels for reporting and discussing real-world events, including health complications and disaster situations. Making use of the massive volumes of data produced on these platforms—especially Twitter—offers a chance to monitor and identify different types of epidemics. In order to accomplish this, a system for identifying tweets connected to epidemics is required, making it possible to predict outbreaks ahead of time. The authors of this study present a deep learning model intended to identify tweets associated with various outbreaks, such as public health issues, epidemics, and natural catastrophes. GloVe (Global Vectors for Word Representation) embeddings are used by the model as the feature extraction method, which makes it possible to extract semantic meanings from the tweets. The authors use Long Short-term Memory (LSTM), a specific Recurrent Neural Network architecture that is well-known for its efficiency in sequence modeling, for classification. In order to represent tweets linked to the outbreak, pretrained GloVe word embeddings were used after the human collecting and curation of tweets. The curated dataset was then used to train a Deep Learning Model using the LSTM technique, and an independent dataset was used to assess the model's performance. The outcomes demonstrate the potential of the suggested deep learning model for accurately forecasting epidemics using social media data by showing that it is a reliable method for identifying tweets connected to outbreaks.

H. "A Comparative Analysis of Machine Learning Techniques for Disaster-Related Tweet Classification"

Abhinav Kumar et al. [8] This study emphasizes how important it is to use Twitter data in emergency situations since important information may be found in disaster-related tweets, which can help government agencies and humanitarian organizations prioritize rescue and relief efforts. Considering the sheer number of these tweets, building a trustworthy classification model is crucial to efficiently classifying them into several groups. The authors of this research examine many deep learning and traditional machine learning algorithms for categorizing tweets about disasters into six groups. To evaluate the efficacy of these models, tests are conducted using four distinct catastrophic events: hurricanes, earthquakes, floods, and wildfires. With F1-scores ranging from 0.61 to 0.88 for deep neural network-based models and 0.16 to 0.80 for traditional machine learning classifiers, the results show that deep neural network-based models perform better than conventional machine learning classifiers. This implies that deep neural network models are quite successful in categorizing tweets about disasters, even for unbalanced datasets, demonstrating their potential to greatly enhance disaster response operations and save lives.

I. "Analysis of Disaster Tweets Using Natural Language Processing"

Thulasi Bikku et al. [9] This study highlights the increasing importance of social media, especially Twitter, as an essential means of communication in times of crisis and calamity. People may quickly communicate information on real-life disasters by using mobile phones and other communication devices, which could potentially save countless lives by notifying others and facilitating critical actions. Numerous businesses are actively engaged in using programming to analyze tweets about emergencies and disasters, providing internet users with insightful information. However, because Twitter data is sometimes unstructured, one of the major hurdles in this endeavor is identifying and differentiating between tweets about disasters and tweets about non-disasters. In order to tackle this problem, this research creates a model that can determine whether a user is disseminating knowledge about a disaster or not. In this study, 10,000 tweets and classifiers make up the dataset. Using Natural Language Processing (NLP) approaches, the proposed Optimized Support Vector Machine (SVM) model preprocesses the data and then creates a classifier model that maximizes accuracy in categorizing tweets connected to disasters. Through the analysis and classification of disaster-related content on social media platforms, our research aids in the development of efficient technologies that improve public safety and disaster response operations.

J. “Combining Self-training with Deep Learning for Disaster Tweet Classification”

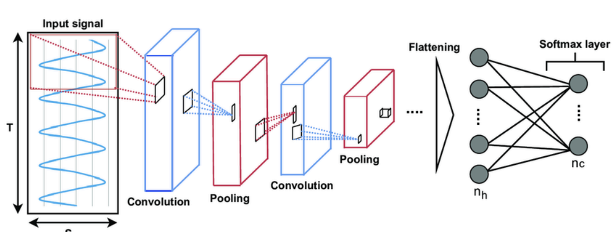
Hongmin Li et al. [10] This study demonstrates the progress gained in automatically classifying tweets connected to disasters through machine learning approaches. For catastrophe tweet classification, a number of deep learning models have been suggested and used independently. These methods include Convolutional Neural Networks (CNN), domain adaptation approaches based on self-training, and pre-trained language models like BERT. But in this study, the authors suggest a novel way to improve the performance of recognizing tweets relevant to crises by combining self-training with CNN and BERT models, especially when labeled data is scarce or nonexistent. The study presents some important conclusions after experimenting with and evaluating three sets of crisis tweets. First of all, it shows that when tuned for downstream crisis tweet classification, the pre-trained language model BERTweet performs better than the normal BERT model. Second, it shows that self-training can greatly enhance the performance of both CNN and BERTweet models, but not as much for smaller datasets. This is especially true for larger unlabeled target datasets. These results highlight the possibility of combining self-training methods with deep learning models to improve the precision and efficacy of tweet identification connected to crises, providing important information for disaster response and management initiatives.

III. METHODOLOGY

The methodology employed in this study involved the development and training of neural network models for the task at hand. The model architecture was constructed using the Keras library. The architecture of each models are as follows:

a) Convolutional Neural Network (CNN)

Example illustration of the model:



Embedding layer: An embedding layer with 10,000 input dimensions and 128 output dimensions was utilized to learn dense representations of input data.

Convolutional layer: It has 128 filters with kernel size 5 and uses the ReLu activation function.

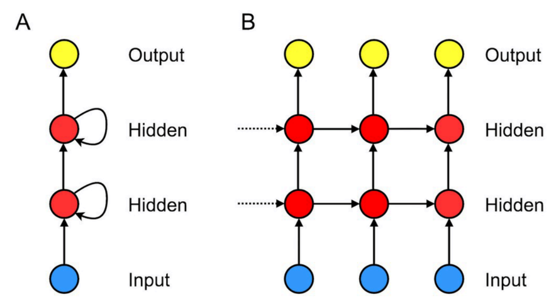
Pooling layer: It uses the global max pooling layer to reduce the dimensionality of the input.

Dense layers: Two dense layers were added subsequently. The first dense layer consisted of 128 units with Rectified Linear Unit (ReLU) activation function to introduce nonlinearity and facilitate feature extraction. The second dense layer consisted of a single unit with a sigmoid activation function, serving as the output layer for binary classification tasks.

Dropout layer: A dropout layer with a dropout rate of 0.2 was inserted between the 2 dense layers to prevent overfitting by randomly setting a fraction of input units to zero during training.

b) Recurrent Neural Network (RNN)

Example illustration of the model:



Embedding layer: An embedding layer with 10,000 input dimensions and 128 output dimensions was utilized to learn dense representations of input data.

RNN layers: First SimpleRNN layer with 64 units and configured to return sequences. This means it returns the full sequence of outputs for each timestep.

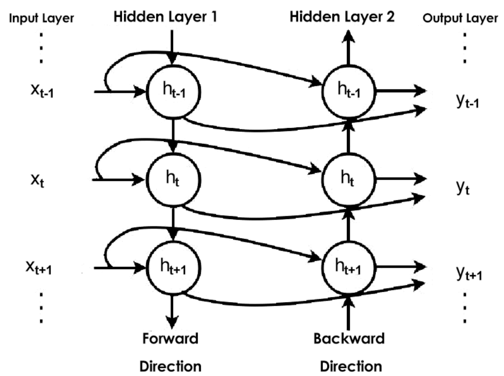
Second SimpleRNN layer with 64 units. This layer doesn't return sequences by default, so it will only return the output at the last timestep.

Dense layers: Two dense layers were added subsequently. The first dense layer consisted of 128 units with Rectified Linear Unit (ReLU) activation function to introduce nonlinearity and facilitate feature extraction. The second dense layer consisted of a single unit with a sigmoid activation function, serving as the output layer for binary classification tasks.

Dropout layer: A dropout layer with a dropout rate of 0.2 was inserted between the 2 dense layers to prevent overfitting by randomly setting a fraction of input units to zero during training.

c) Bidirectional Recurrent Neural Network (Bi-RNN)

Example illustration of the model:



Embedding layer: An embedding layer with 10,000 input dimensions and 128 output dimensions was utilized to learn dense representations of input data.

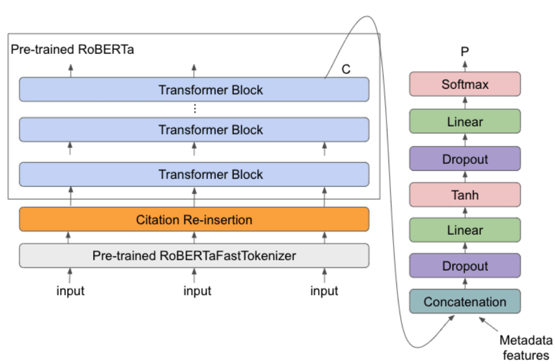
Bidirectional LSTM Layer: Bidirectional wrapper around an LSTM layer with 128 units. The Bidirectional layer processes the input sequence both in the forward and backward direction, accurately capturing information from both past and the future states.

Dense layers: Two dense layers were added subsequently. The first dense layer consisted of 128 units with Rectified Linear Unit (ReLU) activation function to introduce nonlinearity and facilitate feature extraction. The second dense layer consisted of a single unit with a sigmoid activation function, serving as the output layer for binary classification tasks.

Dropout layer: A dropout layer with a dropout rate of 0.2 was inserted between the 2 dense layers to prevent overfitting by randomly setting a fraction of input units to zero during training.

d) RoBERTa (Transformer Model)

Example illustration of the model:



Embedding layer: Converts input token IDs to dense vectors (tensors).

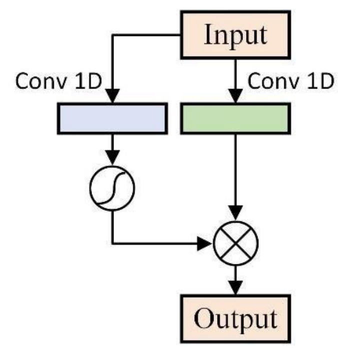
Transformer layers: Consist of multiple Transformer blocks. Each Transformer block consists of: Multi-head self-attention mechanism, feed forward neural network. layer normalization and residual connections around each sub-layer.

Pooling Layer: Aggregates the outputs of all the Transformer layers to generate a fixed size representation of the given input sequence.

Output Layer: Task specific output layers are added on top of the Transformer layers. In this case, the task is binary classification.

e) Gated Linear Unit (GLU)

Example illustration of the model:



Embedding layer: An embedding layer with 10,000 input dimensions and 128 output dimensions was utilized to learn dense representations of input data.

GLU layer: Gated Linear Unit layer with 128 units is added. It is a type of activation function that applies a gating mechanism to the given input sequence.

Dense layers: Two dense layers were added subsequently. The first dense layer consisted of 128 units with Rectified Linear Unit (ReLU) activation function to introduce nonlinearity and facilitate feature extraction. The second dense layer consisted of a single unit with a sigmoid activation function, serving as the output layer for binary classification tasks.

Dropout layer: A dropout layer with a dropout rate of 0.2 was inserted between the 2 dense layers to prevent overfitting by randomly setting a fraction of input units to zero during training.

Once the architecture was defined, the model was compiled using the adam optimizer (rmsprop in one case) and binary cross entropy loss function (as its binary classification). The optimization process aimed to minimize the defined loss function, while the optimizer adapted learning rates for each parameter individually.

The model was trained on the disaster tweets dataset. The training process was conducted for a total of 10 epochs, allowing the model to iteratively adjust its parameters to minimize the training loss and improve its performance.

IV. CORPUS

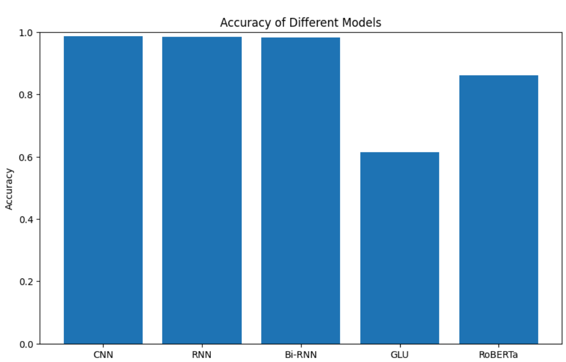
The dataset used in this paper has 4 columns namely, id, keyword, location, text and target. The "id" column is like the primary key which gives a unique number to each tweet. The "keyword" mentions the important word from the tweet which could decide whether the tweet is a disaster or not, this column has null values. The "location" column has the location from where the tweet was sent, this column has null values too. The "text" column has the actual content of the tweet. The "target" column has 0 (not disaster) and 1 (disaster) values filling all the rows. There are a total of 7503 tweets in this dataset.

V. MODEL EVALUATION

The evaluation metric used in this paper is just accuracy. All the 5 models performed pretty well, but one model performed the best when compared to the other models. Since, the dataset wasn't very large the model isn't perfect and there is a tiny bit of overfitting seen. But, still the performance is good.

VI. RESULTS AND DISCUSSIONS

Models	Accuracy
CNN	0.9860764741897583
RNN	0.9848942756652832
Bi-RNN	0.9817417860031128
RoBERTa	0.8616666666666667
GLU	0.6148563027381897



From our research, the best model surprisingly was the convolutional neural network with an accuracy of 0.9860764741897583. Although we had expected the transformer model to be the best, in our case CNN was more accurate.

VII. CONCLUSION AND FUTURE WORK

To sum up, this paper offers a thorough analysis of the creation, training, and assessment of a deep learning neural network model for the specified purpose. The obtained outcomes demonstrate the efficacy of the suggested methodology and model architecture, opening the door for further studies focused on developing machine learning methods for real-world use. This can be further improved in the future by using a larger and more sophisticated dataset and also adding things more than text for example like image data too.

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Google Colab link:
https://colab.research.google.com/drive/1JWtvYFG6JFoNNDIoZKkJ1efA_Qp9X3FP?usp=sharing
Dataset link:
https://www.kaggle.com/competitions/nlp-getting-started/data