Enhanced Classification of Tweets and Emergency Response using BERT with AdamW Optimizer and NER

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Abstract - *Social media sites, particularly Twitter, allow for rapid communication about disasters, they have turned as acute information sources during emergencies. The vital target of this study is the classification of tweets, which employs data from GitHub. The model gains an accuracy of 83.32% in classifying tweets into disaster and non-disaster categories by using Bidirectional Encoder Representations from Transformers (BERT) with the AdamW optimizer. This method outperforms base research that just addressed the identification and categorization of tweets about transportation disasters, and itattained 82% accuracy. Named Entity Recognition (NER) is used not just to classify tweets but also to extract principal entities fromthem, including disaster types, locations, and other pertinent information. This study points the determined location from the tweet on the map and also gives assistance regarding the safety measures and emergency contact details during emergency situations through a chat bot. This data can be instantly used by the government agencies, emergency personnel and can protect the lives of people.*

***Key Words*: Bidirectional Encoder Representations from Transformers (BERT), Named Entity Recognition (NER), Adaptive Moment Estimation with Weight Decay (AdamW), Overfitting, Support Vector Classifier, Decision Tree, Random Forest, XG Boost**

1. INTRODUCTION

Social media sites, peculiarly Twitter, have become crucial for providing instantaneous updates during crises, as they allow individuals to share significant information, report disasters, and request help [1] , [2]. Social media has turned into a vital instrument in disaster management due to the rapid dissemination of information during emergencies, which facilitates quicker discovery and reaction [3], [4]. It is very much necessary to categorize tweets correctly about disasters because this information can be instantly used by government agencies, emergency personnel, and can protect the lives of people [5]

This study includes cutting-edge Natural Language Processing (NLP) methods to amplify the classification of disaster tweets. Diverse machine learning algorithms were first tested for tweet classification, including Support Vector Classifier (SVC), Decision Trees, Random Forest, XGBoost, and BERT with the AdamW optimizer [6]. The BERT model with the AdamW optimizer was the most successful model for this task, showing the highest classification accuracy of 83.32%. A potent pre-trained language model called Bidirectional Encoder Representations from Transformers (BERT) has illustrated outstanding performance in a range of Natural Language Processing (NLP) tasks, particularly because of its capability to find out the contextual relationships in text [5]. We further improved BERT's performance by fine-tuning it with the AdamW optimizer, which resulted in high accuracy in classifying tweets concerned with disasters [8]. The accuracy attained in this study surpasses the 82% accuracy in an earlier study that considered tweets about transportation disasters [6].

1.1 OBJECTIVES

Classification of Tweets into Disaster or Non- Disaster Tweets: To differentiate tweets into disaster- related or non-disaster related, diverse machine learning algorithms were utilized, like SVC, Decision Tree, Random Forest, XGBoost and BERT with AdamW optimizer [5]. Out of them, BERT with AdamW Optimizer had given the maximum accuracy [6].

Information Extraction Using Named Entity Recognition (NER): Named Entity Recognition (NER) is employed to find out the principal elements such as disaster categories, affected localities, and other crucial facts from tweets [3], [7]. To support the process of disaster management, NER is implemented as a dominant instrument for obtaining organized data [5].

Location Data on Disasters Visualized Geographically: The geographic locations taken from the tweets regarding disasters are pointed onto a map which will enhance the emergency response tactics [7], [6], [8].

Chatbot Integration for Emergency Response: A chatbot is integrated that will present the emergency helpline details and protective measures to be taken during the times of disasters [8].

2. LITERATURE SURVEY

Social media has become an essential tool for communicating in real time and sharing information during emergencies in recent years. Platforms such as Twitter are crucial for crisis management because they enable users to share updates, report events, and ask for assistance in a matter of seconds. Researchers in the fields of natural language processing (NLP), machine learning, and geospatial analysis are very interested in the growing amount of social media data during emergencies. Understanding the development of techniques for extracting, classifying, and using such data is crucial for developing an efficient catastrophe tweet classification and response system.

This section offers a thorough analysis of the body of research on keyword detection, topic segmentation, sentiment analysis, geolocation extraction, and contemporary transformer-based models, including their optimization and integration with emergency services. It is arranged both chronologically and methodologically.

Early Research on Disaster Detection: Early research investigated the use of social media, especially Twitter, as a platform for disaster-related real-time event detection. Sakaki et al. [9] showed how social sensors can be used to quickly identify catastrophic events by presenting a technique for real-time earthquake detection using Twitter conversations. This effort contributed to the expanding field of using crowdsourced data for real-time disaster management by becoming the first to use social media for early disaster detection.

Using Twitter to Find Pertinent Disaster Messages: A system for selecting pertinent tweets that could help with disaster management was proposed by Cobo et al.[1], who also looked into the potential of Twitter- based citizen channels for natural disaster scenarios. Their strategy centered on how crucial it is to sort through and discover messages in the vast amount of social media data produced by natural disasters.

Geoparsing and Location Extraction: The precise extraction of location data from social media is an essential component of disaster management. In order to identify disaster areas and provide geographical context, Middleton et al. [3] investigated techniques for location extraction from social media posts using geoparsing, location disambiguation, and geotagging. The integration of location-based data into disaster management systems was made possible by their efforts.

Monitoring Disasters using Recurrent Neural Networks: Recurrent neural networks (RNNs) and word embeddings were used by Hernandez-Suarez et al. [4] to track the social dynamics of natural disasters. Their method helped to trace the development of natural catastrophes in real-time by demonstrating how deep learning techniques may be applied to Twitter data to obtain insights about disaster situations.

Classification Using Machine Learning and Deep Learning Methods: In order to categorize tweets about disasters, Asinthara et al. [5] used both machine learning and deep learning approaches. Their study demonstrated how well deep learning models handled the intricacy of unstructured Twitter data, underscoring the necessity of more sophisticated models like BERT for upcoming disaster detection jobs.

Transformer and BERT Models for Crisis Categorization: For text classification challenges, BERT (Bidirectional Encoder Representations from Transformers) has gained popularity. Crisis BERT, a robust transformer model created especially for crisis classification and contextual crisis embedding, was presented by Liu et al. [2] This model fared better than conventional machine learning methods, which makes it ideal for handling complicated, big disaster datasets like tweets.

Modelling Topics for Public Involvement: Topic modeling was used by Ahn et al. [7] to investigate Twitter user participation during the 2019 Ridgecrest earthquake. In order to help agencies evaluate the social dynamics of a crisis, this study demonstrated how Twitter may be used as a platform for measuring public mood and engagement during natural catastrophe situations.

Emergency Assistance Chatbots: A cloud-based chatbot named SPeCECA was proposed by Maalel et al. [8] that offers intelligent support in emergency situations. The chatbot was created to provide vital emergency information and safety guidelines, highlighting how interactive technology may improve the effectiveness of catastrophe response.

Multimodal Analysis of Disaster Tweets: Gautam et al. [10] investigated multimodal analysis of tweets about disasters, taking into account user-shared photos and videos in addition to textual material. Their method increased the overall accuracy of disaster categorization systems by creating new opportunities for the integration of visual data in disaster analysis.

Recognizing Eyewitness Testimonies: Techniques for automatically recognizing eyewitness tweets during disasters were developed by Zahra et al. [11]. Their efforts improve the quality of data utilized for crisis management by helping to separate first-hand reports of disasters from general reporting.

Identifying Emergencies Using Social Media Information: With Sakaki et al. [9] leading the way in this field, the capacity to recognize catastrophes through social media has developed into an essential instrument for disaster response. Their ground- breaking study investigated the use of social media sites like Twitter for real-time earthquake detection. They created algorithms that could instantly scan tweets for trends that might point to an emergency. Sakaki et al.'s research showed that social media data, particularly location-tagged tweets, might be used to monitor the occurrence and spread of earthquakes and other natural catastrophes nearly immediately after they happen. The potential of "social sensors"—a term used to characterize how the collective activity of social media users can yield a plethora of information that is more rapid and dynamic than traditional reporting methods—was underlined by their study. For instance, Twitter's quick and extensive use can serve as an unofficial but very powerful sensor network, warning authorities of incidents before the official emergency services have a chance to react. Sakaki et al. were able to create a model that could automatically categorize tweets as being connected to an emergency occurrence by looking at the linguistic patterns in tweets (such as the usage of phrases like "earthquake," "shaking," or "damage") as well as metadata like time and location. The accuracy and speed of crisis identification utilizing social media are continuously being improved by increasingly advanced methods, such as those based on BERT (Bidirectional Encoder Representations from Transformers), which were made possible by this architecture.

Disaster Relief Using Social Media and Crowdsourcing: Gao et al. [12] looked studied how crowdsourcing can be used for disaster aid on social media sites like Twitter. Their study demonstrated how social media real-time data could help local disaster response initiatives

3. METHODOLOGY

Gathering and preprocessing data: The study's dataset, which included tweets with matching id, keyword, location and target columns. In the binary target column, 0 signify tweets that are not related to disasters and 1 signify that the tweets are related to disaster [6], [5]. Figure 1 is the sample dataset that is used for this study. The classification models are trained and assessed using this dataset as the basis. Although the raw tweets are initially supplied in a structured CSV file, preprocessing is necessary to make the text content suitable for model training.

Id	Keyword	Location	Tweet	Target
1	ablaze	Birmingham	@bbcmtd Wholesale Markets ablaze http://t.co/lHYXEOHY6C	1
2	accident	Charlotte	9 Mile backup on I-77 South...accident blocking the Right 2 Lanes at Exit 31 Langtree Rd...consider NC 115 or NC 150 to NC 16 as alternate	1
3	ambulance	Loveland Colorado	@Kiwi_Karyn Check out what's in my parking lot!! He said that until last year it was an ambulance in St Johns. http://t.co/hPvOdUD7iP	0
4	annihilated	Boston	Cop pulls drunk driver to safety SECONDS before his car is hit by train. http://t.co/tHrhKHOGcUåÊ http://t.co/tZSZmF2qxE via @ViralSpell	1
5	attack	India	Militants attack police post in Udhampur; 2 SPOs injured | LiveMint http://t.co/Rptouz2iJs | http://t.co/69mLhfefhr #AllTheNews	1
6	attack		Heart disease prevention: What about secondhand smoke? http://t.co/YdgMGBrYL2	0
7	avalanche	Ireland	A little piece I wrote for the Avalanche Designs blog! I'd appreciate it greatly if you checked it out :-) https://t.co/rfvjh58eF2	0
8	blaze		Columbus, OH",UGH Y DID BLAZE PUT THE CALORIES BY THEIR PIZZAS? OK COOL #thisispublichealth	0
9	blood	Indonesia	it wasnt a very big stab but it was a deep stab and theres like blood everwhere	1
10	blight	Scotland	LIKE I SWEAR THE SECRET WE'LL UNCOVER IS THE OLD GODS IN A SLUMBER. I THINK THERES GONNA BE ANOTHER BLIGHT	0

Fig -1: Twitter dataset collected from GitHub

***Data Preprocessing*:** To raise the quality of the content, URLs, special characters, punctuation, and stop words were eliminated. Just the tweet text was kept for processing [3]. Lowercasing: To maintain consistency, all tweets were changed to lowercase [10]. Word Piece Tokenization was used to break down tweets into sub word tokens in accordance with the BERT model's requirements [5]. Dealing with Missing Values: Tweets which contain null or empty values were dropped from the tweet column [6]. Balancing Data: Used oversampling and under sampling approaches to address the class imbalance between tweets about disasters and those that weren't [5].

Model Selection and Comparison: Diverse machine learning models were assessed in order to determine which one was best for tweet classification:

Support Vector Classifier (SVC): Divides the tweets into disaster and non-disaster categories using a hyperplane-based methodology. Enhances classification resilience on high-dimensional twitter data by optimizing the margin between classes. For processing textual data, Non-linear classification is made possible by effective kernel methods [10].

Decision Tree Classifier: By dividing data according to feature values, the Decision Tree Classifier creates a tree-based model with logical decision paths. The significance of features is measured by revealing which tweet features have the biggest impact on classification. It provides interpretability and simplicity of visualization for both numerical and category data [11].

Random Forest Classifier: Improves classification stability and accuracy by combining predictions from several decision trees. By employing bagging approach, it reduces overfitting which works especially well with noisy social media data. It provides balanced predictions and resilience to missing data and outliers [4].

The XGBoost Algorithm: Uses extreme Gradient Boosting, a potent ensemble classification technique. It handles intricate tweet patterns with effectiveness by upgrading weak learners iteratively. It enhances the model generalization and minimizes the chances of overfitting by employing built-in regularization [5].

Bidirectional Encoder Representations from Transformers (BERT) was implemented and optimized using the AdamW optimizer: Surpassed both the 82% accuracy of the base paper, which only looked at tweets on transportation disasters and conventional ML models to get the greatest accuracy [6]

Model Selection Criteria: Because of its contextual awareness, exceptional accuracy and ability to analyse the text in both directions, BERT with AdamW was chosen [2] [5] [6] Robust generalization and quicker convergence were facilitated by the AdamW optimizer [6].

BERT Implementation Using AdamW Optimizer: One of the most sophisticated models in Natural Language Processing (NLP) is BERT (Bidirectional Encoder Representations from Transformers), which is renowned for its potent transformer-based design. BERT has a richer comprehension of word context since it processes text in both directions concurrently, in contrast to typical models that process text either from left-to- right or right-to-left. BERT excels at fine-grained classification tasks, including tweet categorization for disaster-related information, because of its bidirectional nature [5], [6].

Data must be converted into an appropriate input format before being fed into BERT. Tokenization with Word Piece, which divides words into sub word units to better handle uncommon or unknown terms, is one example of this. Three additional kinds of embeddings are also applied to the input: position embeddings, which preserve the sequential order of the tokens, segment embeddings, which distinguish various sentences, and token embeddings, which represent each word or sub word. The input sequences are marked and aligned evenly using special tokens such as [PAD] (padding token), [SEP] (separator token), and [CLS] (classification token) [5], [6]

The Transformer Encoder, which is the central component of BERT's design, computes associations between each word in the sequence using a self-attention process, enabling the model to comprehend each word's complete context. Furthermore, elements such as layer normalization, feed-forward networks, and residual connections aid in stabilizing training and promoting convergence [5], [6]

There are two steps in the learning process for BERT. It employs the Masked Language Model (MLM) technique in the pre-training stage, in which 15% of the input tokens are masked and the model learns to predict them based on contextual information. This helps BERT gain a strong grasp of language in both directions. Furthermore,

BERT determines if a sentence logically follows another by using Next Sentence Prediction (NSP). This facilitates BERT's performance on sentence-level tasks like question answering and tweet-event association [5], [6]

The model's output from the [CLS] token is connected to a classification head, usually a fully connected layer, which outputs the probability of whether a tweet is related to a disaster or not. This allows BERT to be fine-tuned for disaster tweet classification. When compared to conventional machine learning models, this configuration greatly increases classification accuracy by allowing BERT to produce precise predictions on domain-specific tasks [5], [6]

The reason for including AdamW optimizer with BERT: The AdamW optimizer was incorporated to improve BERT's functionality and training effectiveness. Decoupled weight decay regularization, which AdamW introduces, is crucial for avoiding overfitting and regulating excessive weight gain during training. Its hybrid technique, which combines the advantages of Momentum and Root Mean Square Propagation (RMSProp), also promotes improved convergence. Faster training and efficient handling of sparse gradients—which are prevalent in twitter data—are the outcomes of this. Additionally, AdamW is memory-efficient, which makes it appropriate for handling massive datasets, such as tweets about disasters [8], [6].

Named Entity Recognition (NER): Named Entity Recognition (NER), which helps recognize specific entities like disaster categories (e.g., earthquake, flood), geographical locations, and other pertinent phrases, is essential for extracting important information from tweets about disasters. Because of its better contextual comprehension of natural language, BERT was used in this study to develop token-level NER. The model efficiently separates and classifies important information from unprocessed twitter text by giving each token a name, such as LOC for location, DISASTER for crisis category, or O for other irrelevant tokens [5][6]

The loud, unstructured material seen on social networking sites like Twitter is a common problem for traditional NER algorithms. But unlike previous models, BERT can disambiguate tokens more precisely because of its bidirectional transformer architecture, which allows it to comprehend the context around each word. For example, the word "fire" in "forest fire" is obviously a calamity, yet it is not in "she fired him." BERT's simultaneous processing of preceding and succeeding context enables this kind of disambiguation [5].

Additionally, NER's integration into the tweet- processing pipeline facilitates location-specific warnings and event detection, both of which are essential in the early phases of disaster response. The method can assist authorities prioritize actions by highlighting not only the location of a crisis but also its type. NER significantly boosts the usefulness of social media in emergency situations by turning unstructured social media conversation into organized, actionable information [5], [6].

Information Extraction and Visualization: Mapping Locations- NER module is utilized, using which the location entities were taken from the tweet. It was then used by Streamlit to map these places spatially, giving a visual sketch of the areas affected by disasters [3], [5], [6]

Integration of Emergency Contacts: The Chatbot that is integrated provided useful information in times of crisis by presenting emergency contact details as per the location and kind of disaster [5], [6]

Streamlit App Development: Streamlit was used to create an interactive Graphical User Interface (GUI), with the following essential features:

Tweet Classification: Using the BERT with AdamW model, users can categorize tweets as either disaster-related or not [5], [6].

Named Entity Recognition (NER): Used in entity extraction to find vital entities in tweets, including disaster types, locations, and other pertinent information [5], [6]

Geographical Mapping: Provides geographical insights into areas affected by disasters by visualizing the extracted places on the map [5], [6].

Emergency Contact Integration: Provides rapid access to vital support services by displaying pertinent emergency contact information based on the designated catastrophe site [5], [6].

Metrics for Evaluation:

Accuracy: Evaluated the model's overall correctness in categorizing tweets as either non- disaster or disaster.

Precision: Measuring the percentage of correctly detected catastrophe tweets among all tweets classed as disasters indicates the specificity of the model.

Recall (Sensitivity): Assessed the model's comprehensiveness by determining its capacity to identify real-world disaster tweets.

F1 Score: A balanced metric for unbalanced datasets, it is computed as the harmonic mean of precision and recall.

Confusion Matrix: Provides information on misclassification trends by visualizing true positives, true negatives, false positives, and false negatives.

Comparison with Base Paper: Expanded the base paper's scope to include a greater variety of natural and man-made disasters, rather than just transportation-related ones. Achieved a significant increase in accuracy (from 82% to 83.32%). Demonstrated a comprehensive approach to catastrophe management by adding a unique element for location mapping and emergency response integration [6].

4. STEPWISE PROCESS ILLUSTRATION

The flow diagram in Fig-2 explains various steps in this study that includes, Tweet Classification, Event Extraction, Geographical mapping and Emergency response. This flowchart is extended from the flowchart of the paper in reference [6]. About 10,000 tweets are collected as a dataset. These tweets provide unprocessed data. Preprocessing is done on the gathered tweets, which includes eliminating unnecessary text, URL's, stop words, noise, and special characters [3], [10]. Vector Space Model: Embedding Words-The cleaned text is converted into a numerical representation using a word embedding approach for preparing the data for further steps [5]

Entity Extraction Using Named Entity Recognition (NER): NER is used to extract principal details from tweets, including locations, phrases related to disasters, and other pertinent details. [3], [10], [11]

Model Creation and Training: Eighty percent of the dataset is used to train the model. Tweets are classified using a diverse machine learning and deep learning techniques, including SVM, Decision Tree, Random Forest, XGBoost, and BERT with AdamW Optimizer [5], [6]. The remaining 20% of data is used for testing the trained model. Whether a tweet is related with a disaster or not is predicted by the model [2], [6].

Using Maps to Point the Location: The place extracted from the tweet is pointed on the map [3], [10]

Chatbot Interaction for Emergency Response: The chatbot assists in gathering emergency contact information to ensure appropriate actions are taken [2], [8]. All the above discussed steps are pictorially presented in the form of a flowchart. BERT with AdamW Optimizer is opted for this study as it resulted in greater accuracy when compared to other algorithms [5], [6]. Only if the tweet contains the location, then it is visualized on the map, else the location is not mapped on the map.

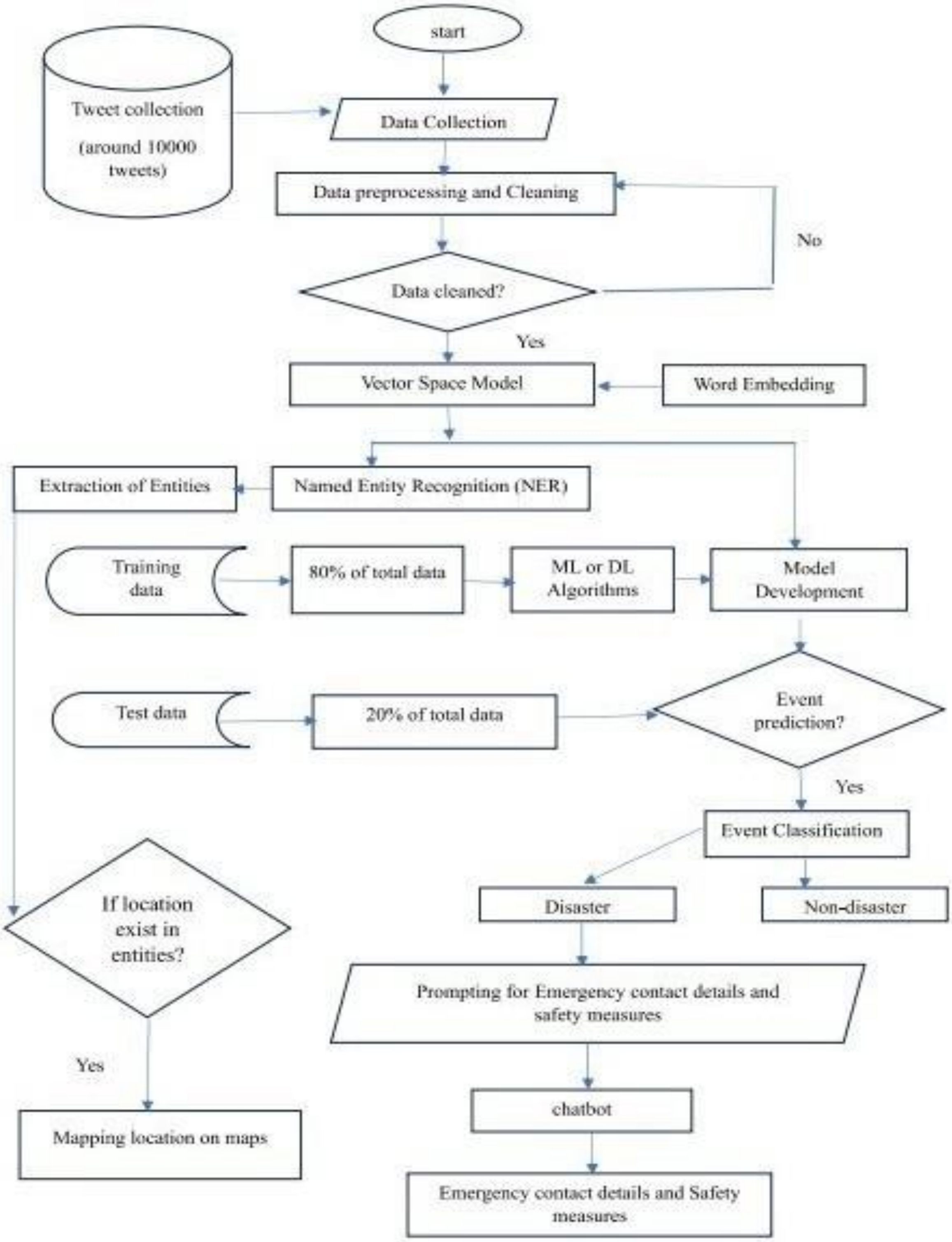

Fig – 2: Flow diagram

5. EVALUATION DETAILS AND RESULTS

The first objective is to classify tweets either non- disaster related or disaster relevant using classification. First, conventional machine learning models like XGBoost, Random Forest, Decision Tree, and Support Vector Classifier (SVC) were evaluated [5], [6]. After that, the BERT model with the AdamW optimizer was used, and it has given better results [5], [6].

The second goal was to identify disaster types, locations, and other pertinent information by employing Named Entity Recognition (NER) techniques to extract important entities from the tweets [3], [10], [11]. The third goal was to map the extracted places geographically in order to give context and a visual depiction of areas that are vulnerable to disasters [3], [10]. By providing suitable emergency contact information concerned to the labelled calamity sites, the fourth goal sought to improve emergency response and support public safety and efficient disaster management [2], [8].

Training and Optimizing Models: BERT with AdamW optimizer model was refined with the dataset of tweets. By modifying weight decay and learning rates, the AdamW optimizer enhances model correctness and facilitates effective gradient updates [5], [6]. Three epochs of training were carried out, with early termination to avoid overfitting [5].

Principal Findings: Conventional Classifiers were outperformed by a Transformer-based model, BERT with AdamW model which demonstrated superior accuracy and a well-balanced trade-off between precision and recall [5], [6]. The utility of pre-trained language models like BERT was highlighted by the fact that traditional machine learning models, although they produced respectable results, had trouble with complex tweet contexts [2], [6].

For visualizing the tweet classification, entity extraction, location mapping, and emergency response, a Streamlit app was created for this study which offers an interactive and inherent graphical user interface (GUI [8], [10]).

Users of the app can:

1. Decide whether a tweet is about a disaster or not [5], [6].
2. NER approaches are used to extract entities, such as locations and disaster types [3], [10].
3. See the locations that have been extracted on an interactive map.[3], [10]
4. Present emergency contact information pertinent to the designated catastrophe sites [2], [8]

When the tweet was provided as input, for example consider, "Earthquake occurred in Warangal." With the help of an ambulance horn symbol and a sad face emoji, the streamlit software successfully categorized the tweet as disaster-related, highlighting the gravity of the situation [5]. Using the Named Entity Recognition (NER) portion, Warangal was accurately extracted as the place. Warangal was graphically located on the interactive map by the Mapping Location feature, which gave the catastrophic occurrence of a geographical context [3], [10].

Also integrated a chatbot that will provide assistance in emergency situations by providing safety instructions and pertinent emergency contact information when asked, "Earthquake occurred in Warangal, give me safety tips and emergency contact phone numbers"[2], [8].

Model	Accuracy	Precision	Recall	F1 Score
Support Vector Classifier (SVC)	78.79%	79%	86%	82%
Decision Tree	71.24%	76%	74%	75%
Random Forest	76.42%	78%	81%	80%
XGBoost	77.02%	75%	91%	82%
BERT with AdamW	83.32%	83%	89%	86%

Fig – 3: Comparison of different Classifiers

Fig - 3 shows the comparison of different classifiers and their results by considering accuracy, precision, recall and F1-score. From that, it is clear that BERT with AdamW has greater accuracy, precision, recall and F1-Score when compared to other classifiers [6].

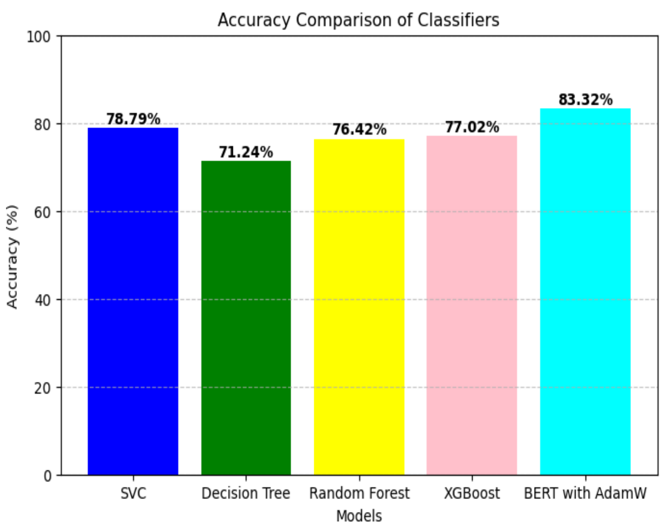

Fig – 4: Accuracy Comparison of different classifiers

A bar graph comparing the accuracy of different classifiers is shown in Fig - 4. The graphic makes it clear that the accuracy of the BERT model optimized with AdamW is noticeably higher than that of the other models [5], [6].

Fig - 5: Output of Classification and Entity Extraction oftweets

The entity extraction and classification modules process the input tweet "Earthquake in Warangal" in Fig - 5. The tweet is correctly identified by the model as being about a disaster [5], [6]. Additionally, "Warangal" is effectively recognized as a place entity by the Named Entity Recognition (NER) system [3], [10]. The system's capacity to accurately classify tweets and extract vital information for disaster reaction and management is shown in Fig – 5, [3], [10], [11].

"Earthquake in Warangal" is an example of a tweet that has had its location retrieved and shown on an interactive map in Fig- 6. A clear spatial context of the disaster is provided by the identification and plotting of the geographical entity (Warangal) on the map [3], [10]. This provides instant insight into the area affected by the event and makes it easier for users to identify the affected region [3], [10], [11].

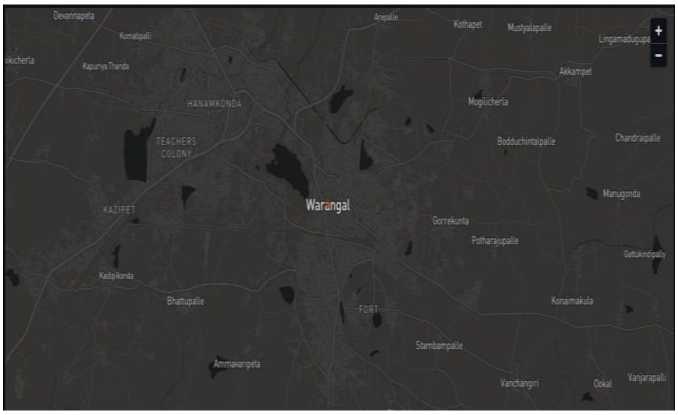

Fig – 6: Extracted Location pointed on the map

6. DISCUSSION

Using the BERT model with the AdamW optimizer and Natural Language Processing (NLP) approaches, this study offers a reliable method for disaster analysis from tweets [5], [6]. The principal objectives were to categorize tweets as either catastrophe-related or not, precisely extract entities like locations and types of disasters, and offer a geographic map of disaster sites along with emergency contact details [3], [5], [10]. By using Named Entity Recognition (NER), this study improved the model's capability to display location- based data, as a substitute to extract location information straight from the tweet text [3], [10].

With an impressive accuracy of 83.32%, the BERT model with the AdamW optimizer outperformed more conventional machine learning models such as XGBoost, Decision Tree, Random Forest, and Support Vector Classifier (SVC) [5], [6]. The addition of the AdamW optimizer improved the BERT model's performance on the unstructured Twitter dataset by reaching greater accuracy, which was attributed to its efficient handling of learning rates and weight decay [2], [5], [6]. Even though SVC demonstrated good accuracy, it is not the best choice for large datasets, which is consistent with the goal of increasing the dataset size in the future [5]. Because of the slow prediction speed of Random Forest model, it was less suitable for real-time applications even if it performed well [5], [6].

The Streamlit-based GUI created for this project allows tweet classification, entity extraction, geographical mapping, and emergency contact information presentation [5], [6]. In addition to making, it easier to obtain the vital information, the visual interface helps in emergency decision-making [5], [6], [8].

7. CONCLUSION

This study used machine learning models and Natural Language Processing (NLP) approaches to create a reliable model for disaster analysis from tweets. Using Named Entity Recognition (NER), the suggested method extracted the entities and locations related to disasters, and the BERT model with the AdamW optimizer is used for tweet. An interactive platform for tweet classification, entity extraction, location mapping, and emergency aid was made available by the Streamlit- based GUI.

When the model's performance was compared to more conventional classifiers like Support Vector Classifier (SVC), Decision Tree, Random Forest, and XGBoost, it showed that BERT and AdamW performed more accurately and efficiently. Together with excellent precision, recall, and F1-score, the classification accuracy of 83.32% highlights how well the suggested model works to identify tweets about disasters.

Additionally, important data like the kind and location of the disaster were successfully recovered by the NER module and displayed on a map in the Streamlit app. By offering safety advice and emergency contact information, the Assistance Bot further enhanced the model's usefulness for disaster response and management.

All things considered, this study demonstrates how effective social media — particularly Twitter — can be for crisis management and detection in real time. The suggested solution provides a thorough method to assist emergency response teams, governmental organizations, and the general public during crisis situations by utilizing cutting-edge natural language processing (NLP) techniques and interactive visualization.

8. FUTURE SCOPE

Extend the Dataset: To enhance model generalization, gather additional tweets and provide a wider range of disaster situations.

Algorithm Exploration: To increase forecast accuracy even more, try out more sophisticated classification models and optimization strategies.

Real-Time Analysis: To enable prompt disaster identification and reaction, use the Twitter API for real time disaster analysis.

Severity Assessment: Create a system to analyse the seriousness of disasters thathave been detected so that emergency response teams can efficiently prioritize their efforts.

REFERENCES

[1] Cobo, A., Parra, D., & Navón, J. (2015). Identifying relevant messages in a Twitter-based citizen channel for natural disaster situations. *WWW '15 Companion: Proceedings of the 24th International Conference on World Wide Web*, 1189-1194. https://doi.org/10.1145/2740908.2741719

[2] Liu, T. Singhal, L. Blessing, and K. L. Wood, “Crisis BERT: A robust transformer for crisis classification and contextual crisis embedding,” in *Proc. 32nd ACM Conf. Hypertext and Social Media (HT '21)*, 2021, pp. 285–295. doi: 10.1145/3465336.3475117T. Sakaki, M. Okazaki, and Y. Matsuo, “Earthquake shakes Twitter users: Real- time event detection by social sensors,” in *Proc. 19th Int. Conf. World Wide Web (WWW)*, 2010, pp. 851–860. doi: 10.1145/1772690.1772777.

[3] S. E. Middleton, G. Kordopatis-Zilos, S. Papadopoulos, and Y. Kompa Tsiaris, “Location extraction from social media: Geoparsing, location disambiguation, and geotagging,” *ACM Transactions on Information Systems (TOIS)*, vol. 36, no. 4, article no. 40, pp. 1–27, Jun. 2018. doi: 10.1145/3202662

[4] A. Hernandez-Suarez, G. Sanchez-Perez, K. Toscano-Medina, H. Perez-Meana, J. Portillo-Portillo, V. Sanchez, and L. J. García Villalba, “Using Twitter data to monitor natural disaster social dynamics: A recurrent neural network approach with word embeddings and kernel density estimation,” *Sensors (Basel)*, vol. 19, no. 7, article no. 1746, Apr. 2019. doi: 10.3390/s19071746

[5] K. Asinthara, M. Jayan, and L. Jacob, “Classification of disaster tweets using machine learning and deep learning techniques,” in *Proc. 2022 Int. Conf. Trends in Quantum Computing and Emerging Business Technologies (TQCEBT)*, Pune, India, Oct. 13-15, 2022. doi: 10.1109/TQCEBT54229.2022.10041629

[6] Prasad, R., Garg, A. K., Udeme, A. U., Misra, S., & Bisallah, H. (2023). Identification and classification of transportation disaster tweets using improved bidirectional encoder representations from transformers. *International Journal of Information Management Data Insights, 3*(1), 100154. https://doi.org/10.1016/j.jjimei.2023.100154

[7] J. Ahn, H. Son, and A. D. Chung, “Understanding public engagement on Twitter using topic modeling: The 2019 Ridgecrest earthquake case,” *Journal of the Japanese Society for Information and Media Studies*, vol. 30, no. 2, article no.100033, 2021. doi: 10.1016/j.jjimei.2021.100033

[8] A. Maalel, N. Ouerhani, and H. Ben Ghezala, "SPeCECA: A smart pervasive chatbot for emergency case assistance based on cloud computing," *Cluster Computing*, vol. 23, no. S1, pp. 1–12, Dec. 2020. doi: 10.1007/s10586-019- 03020-1.

[9] A. Gautam, L. Misra, A. Kumar, and K. Misra, “Multimodal analysis of disaster tweets,” in *Proc. 2019 IEEE Fifth Int. Conf. Multimedia Big Data (BigMM)*, 2019, pp. 1–8. doi: 10.1109/BigMM.2019.00-38

[10] K. Zahra, M. Imran, and F. Ostermann, “Automatic identification of eyewitness messages on Twitter during disasters,” *Information Processing & Management*, vol. 57, no. 1, article no. 102107, 2019. doi: 10.1016/j.ipm.2019.102107

[11] T. Sakaki, M. Okazaki, and Y. Matsuo, “Earthquake shakes Twitter users: Real-time event detection by social sensors,” in *Proc. 19th Int. Conf. World Wide Web (WWW)*, 2010, pp. 851–860. doi: 10.1145/1772690.1772777.

[12] O. E. Akerele-Popoola, A. L. Azeez, and A. Adeniyi, "Twitter, civil activism, and EndSARS protest in Nigeria as a developing democracy," *Cogent Social Sciences*, vol. 8, no. 1, article no. 2095744, Jul. 2022. doi: 10.1080/23311886.2022.2095744

[13] H. Gao, G. Barbier, and R. Goolsby, "Harnessing the crowdsourcing power of social media for disaster relief," *IEEE Intelligent Systems*, vol. 26, no. 3, pp. 10–14, Jul. 2011. doi: 10.1109/MIS.2011.52

[14] O. D. Apuke and B. Omar, "Fake news and COVID-19: Modelling the predictors of fake news sharing among social media users," *Telematics and Informatics*, vol. 56, article no. 101475, 2020. doi: 10.1016/j.tele.2020.101475