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Identification and classification of transportation disaster tweets using improved bidirectional encoder representations from transformers

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A R T I C L E I N F O

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A B S T R A C T

Social Media today has become the most relevant and affordable platform to express one's views in real-time. The #Endsars protest in Nigeria and the COVID-19 pandemic have proven how important and reliant both government agencies and individuals are on social media. This research uses tweets collected from Twitter API to identify and classify transportation disasters in Nigeria. Information such as the user, location, and time of the tweet makes identification and classification of transportation disasters available in real-time. Bidirectional Encoder Representations from Transformers (BERT) uses a transformer that includes two separate mechanisms, a decoder that produces a prediction for the task and an encoder that reads the text input. It learns contextual relations between words (sub-words) in a text. This research applied BERT with a combination of AdamW optimizers. AdamW is an improved version of stochastic gradient descent that computes an adaptive learning rate for each parameter. Our proposed model produces an accuracy of 82%. It was concluded that our approach outperformed the existing algorithm: BERT having an accuracy of 64%.

Introduction

Social media (SM) has proven to be the most effective tool for real-time event communication. It is more immediate and real-time than the traditional news media channel. SM platforms such as Twitter, Snapchat, and Facebook (Lakhiwal & Kar, 2016) have become part of the daily life of individuals (Sharma et al., 2022) (Mahdikhani, 2022) (Kar, 2021). In the past, Twitter is being used comprehensively in the field of natural disasters and human-made disasters like transportation disasters, earthquakes, diversions, floods, fire, road repair, terrorist attacks, civil unrest, road riots, and so on (Li et al., 2018). The Government and non-Government agencies in Nigeria use Twitter as a news medium in the case of emergencies so that different rescue agencies can be deployed effectively. Twitter is used to achieve real-time road traffic monitoring (Li et al., 2018) (Saeed et al., 2019), event localization, and in numerous location-based services (Kumar & Singh, 2019). Detecting the exact location information of crisis from tweets effectively is a great concern, especially in places where geolocations are turned off. The Twitter platform has three fields for the purpose of information: (1) The location, the user is tweeting from (2) The place mentioned in the tweet (3) The Geo-coordinate. The field for the user location contains 140 characters where the user can input their home address, and this is done while creating the user profile. The user address is not a compulsory field, and, the user can decide to write any random words there or even leave it unanswered.

Many Nigerians prefer to keep their "user location" private on Twitter for the following reasons: (1) They do not find it important, and (2) They prefer to maintain privacy as the social media environment contains both the good and the bad. However, the field here cannot be used as the present user location as it is inputted at the time the user creates the user profile, most time; the user relocates without updating their locations. The second field shows the "name of the place," which is selected before the tweet is sent. An array of longitude-latitude and the location name is used to represent the name of the place. These location names are predefined on the database of Twitter, though this cannot be used as a determinant of the location information as a user can select another location. Authors in Jurgens et al. (2015) realized that 47.33% of tweets only contains place name. Furthermore, out of the 47.33% of the tweet, 13% containing the names of places are incorrect following the spatiotemporal information. The geo-coordinate is the third field (The LAT/LONG of the geographical footprints) which is not compulsory and sometimes included when sending tweets. Researchers in Do et al. (2017) consider the most precise location information to be geo-coordinates, i.e. tweets containing the LAT/LONG information. Although geo-coordinates can be inconsistent in tweets, authors in Gruebner et al. (2018) realized that only 7.9% of tweets are

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rightly geotagged. Further reports state that while geo-coordinates are the most accurate amongst the two, it is not frequently actual about the information of their spatiotemporal whenever tweets are sent from another party application like snap chat. Therefore, each piece of information for location in Twitter account users has its disadvantages.

The problem here involves reducing transportation accident emergencies in Nigeria by identifying in real-time using Twitter API location and further detecting and classifying the severity of the accident. This information will enable the Government agencies to disperse assistants at the proper time and proper place. An important factor in the identification process is finding the exact location of the transportation disaster and providing results with increased accuracy and reducing response time. Previous research on disaster identification and classification using tweets retrieved location data that uses the embedded geographic information provided by Global Positioning System (GPS). Unfortunately, by default, the feature GPS gets disabled by many Twitter users in Nigeria, leading to the option of Named Entity Recognition (NER).

Research questions

The following are research questions pertaining to our study:

i. What are the problems in identification of location of the disasters?
ii. How to classify a tweet into disaster and non-disaster?
iii. How accurate a model is in predicting the disaster?

Aim and objectives

This research aims to propose a model to successfully identify locations with transportation disasters via Twitter, classify them into a disaster or non-disaster and improve their accuracy. Tweets collected from Twitter API were preprocessed and cleaned using term frequency-inverse term frequency (TF-IDF). The following are objectives:

i. NER is used to *identify* transportation disaster by analyzing the tweet text alongside the location database.
ii. Bidirectional Encoder Representations from Transformers (BERT) with AdamW optimizer is used to *classify* tweets into disaster and non-disaster classes.
iii. Performance of proposed model is compared with existing state of art algorithm in the literature.

BERT uses a transformer that includes two separate mechanisms, a decoder that produces a prediction for the task and an encoder that reads the text input. It learns contextual relations between words (subwords) in a text. AdamW is a variant of the Adam optimizer that has an improved implementation of weight decay and computes an adaptive learning rate for each parameter. Our proposed model produces an accuracy of 82%. It was concluded that our approach outperformed the existing algorithm: BERT having an accuracy of 64%.

This research improves the accuracy of the existing BERT model (Hayashi et al., 2016) by integrating AdamW optimizer in BERT. NER was used to identify the location of the disaster as GPS has limitations. The paper can be useful to the Federal Emergency Management Agency (FEMA), and local jurisdictions impacted by a disaster. The research is also useful to researchers working in the area of social media and its uses in disaster management. It is expected that this research will contribute to improving the transportation emergency situations in Nigeria with greater accuracy by sending real-time road traffic and disaster tweets, thereby serving as a tool for the transportation agency in Nigeria.

The paper is divided into the following sections. Section 1 gives the introduction. Here the research background is discussed, and the statement of the problem, the aim, and objectives, and the expected contributions are explained in detail. Section 2 presents the literature review and related concepts. Section 3 discusses the materials and methods used in the research. Section 4 discusses the results and evaluation of this research. The aims of the empirical study are stated, and the result is analyzed. Section 5 discusses the conclusion and future works.

Related work and background

This section describes the related work and background on the use of SM in disaster management, event detection methods, and existing method BERT.

Several organizations (academia and corporate), have started to explore the possibilities of social media, especially Twitter, as a tool for event/disaster management (Kumar & Singh, 2019; Strycharz et al., 2022). Authors in Kumar and Singh (2019) did comprehensive research on Twitter-related papers and realized that about 46% of the research had to do with detecting events, while 13% was about estimating the location; about 27% of the research was related to the detection of events in emergency situations. Recently, increasing works on social media for disaster rescue purposes have been done for efficient usage (Strycharz et al., 2022).

Disaster management and social media

Social media has become a major tool in disaster management, especially in a country like Nigeria which has little to no effective response to transportation disasters in the country. The citizens are solely dependent on information provided by others via social media. For example, the #endsars protest that happened in 2021, a lot of traditional media couldn't report the event as it was (Akerele-Popoola et al., 2022). Citizens were mostly dependent on the social media. The very ethos of social media is to put 'decision making' in the hand of the reader (Olaleye et al., 2022). As a result of the heavy presence of individuals on social media, it is common for individuals to leave digital footprints and personal data online (Haddow & Haddow, 2014).

Government and business organizations are using social media, especially Twitter to gain insights for enlightening performance across different tasks (Rathore et al., 2017). Accurate information distributed to the public, Government officials, and individuals reduces risk, saves lives and property, and speeds recovery (Lomotey et al., 2022). Data sharing is a valuable resource for realizing multi-partner institution goals (Chang et al., 2012), and can also be described as the new asset class (Middleton et al., 2018). Researchers and Organizations can collect and process such data both online and offline and use the information as input for automated decision-making (Haddow & Haddow, 2014). Twitter is mostly used to disseminate information during disasters (Disinformation & coronavirus | Lowy Institute, 2022) and was really useful in disseminating public health information during the COVID-19. Although this vagueness allowed for misinformation and lies to proliferate alongside public health authority's claims (Compton et al., 2014). Filtering the information from social media is the next most important step, fake and unverified news is fast becoming a worldwide concern (Apuke & Omar, 2021). These social media platforms are mostly used for both communication and content consumption. Managing misinformation is therefore a challenge for both the platform and policymakers (Aswani et al., 2019). The different social media platform has put algorithms in place to reduce the spread of fake news, although this is helpful but cannot effectively curb fake news (Updating our approach to misleading information, 2022) (McCormick et al., 2017).

Event detection and location estimation

A lot of research has been centered on emergency and event detection and determination of location (Saeed et al., 2019) (Yao & Qian, 2021) (Singh et al., 2019). For emergency events, some authors tried to detect an event while it occurred, and some authors classified emergency tweets into a preplanned class for more study (Jelodar et al., 2019). With an estimation of location, researchers work towards finding the event location of the user name from social media. This research is classified into two sub-sections: Event detection and Location estimation.

Event detection

A considerable amount of research on techniques for event detection can be found in Saeed et al. (2019). Different rankings were used to select the tweets that are linked to transportation, disaster victims, and those who volunteered. After which, a first-come, first-serve was proposed. They then proposed a method using machine learning for detecting useful messages in a disaster. After these messages are detected, the system then extracts chunks of useful information from the tweets. Authors in Olanrewaju and Ahmad (2018) introduce Tweedr; this can be described as a Twitter mining tool used for the extraction of information for disaster relief workers and agencies during emergencies or natural disasters. The tweed pipeline contains three main parts such as extraction, classification, and clustering.

Researchers in Yao and Qian (2021) (Singh et al., 2019) (Song & Huang, 2021) analyze how social media can be used for predicting data, helping in times of emergencies, using the context of environmental awareness, promoting health, and disseminating information. Authors in Krishnamurthy et al. (2015) proposed the convolutional neural network (CNN) based on a model used for classifying flood tweets into useful or non-useful classes. The system successfully detected flood events in real-time earlier than the official Government media office announcement.

Location estimation

Some researchers in Jurgens et al. (2015) worked on tweet text containing other metadata, namely: "geo-coordinates," "location of the user", and "place name" to estimate the information of the location. It further shows a detailed description of the network-based approach used to determine the Twitter user's geolocation. Authors in Gruebner et al. (2018) researched a multi-view model for learning that merges the text, metadata features, and network to determine the tweet geolocation. It further proposed a model that integrates the network features that are learned from Twitter and the content to predict the location of a user.

Like other network-based approaches, the authors in Hayashi et al. (2016) attempt to separate the location predicting relationships from the ones serving other functions in Twitter. This is achieved by using the topic trained in the model to specify the relationship type. Another group of researchers (Huang et al., 2019) used tweet text in finding the location. The text in the tweet is then used since: (i) The geotagged tweets are not consistent. (ii) The user's location field cannot be categorized as the present location for the Twitter user since the field is usually out of date. Named entity recognition and Gazetteer-based approaches are two popular models for predicting location references in tweets (Von Daniken & Cieliebak, 2017).

Named entity recognition

Researchers in Devlin et al. (2018) made use of tweet clustering and further made use of a Standford-named entity recognizer to get the names of locations from the text of the tweets. A correlation was found between the location of the user and the location of the event, such as the earthquake in Texas and the 2012 election in New Zealand. Also, the frequently used locations that were found in the cluster were taken as the location of the event. Authors in Eilander et al. (2016) made use of the Twitter data from road traffic in two major locations in Texas and then grouped the tweets by identifying an event in a particular field. The individual tweet was tokenized, and the word was tagged by making use of the part of speech (POS) tagger to predict the names of the location. After tagging the POS, it was further observed that the names of the location were followed by some conjunctive words like between, after, in, and around. The grammar-based rule was further applied to find the place name.

Named entity recognition (NER) in twitter for disaster responses

For a more efficient named entity recognition system, researchers trained with text tweets, enabling them to learn better the named entities that were mentioned. Authors in Apuke and Omar (2021) made use of differently named entity recognizers such as TwitterNLP, OpenNLP9, Stanford NER8, Yahoo!, and PlaceMaker10 to predict the names of locations from disaster-related tweets. To achieve this, they trained Open NLP, and Stanford named entity recognition system by making use of disaster-related tweets; they got 0.902 as an F1 score for the retrained Stanford named entity recognition and for open NLP an F1 score of 0.833. Authors in Eilander et al. (2016) made use of machine learning techniques and NER software to predict places: houses, home addresses, names of location, streets, acronyms of places, buildings, and abbreviations.

Authors in Ahn et al. (2021) developed a system that infers names of the location mentioned in tweets text in an unsupervised manner. Different preprocessing on tweet text was applied, and a POS tagger was used to find the proper nouns. Several researchers made use of the deep neural models. Authors in Gao et al. (2019) used the conventional NER tools to experiment and realized that there was a drop from 0.96 inaccuracy to 0.79 when applied to tweet corpus and news. The situation was solved by restricting the NLP pipeline by beginning with the POS tagging, which goes via the pegging process to named entity recognition.

Authors in Jurgens et al. (2015) proposed an unsupervised two-step named entity recognition model called TwiNER using a web N-Gram corpus alongside Wikipedia. The named entity recognizer TwiNER realized a good result when compared with other conventional NER. TwiNER got 0.419 and 0.772 as the F1-score for two different datasets that are ground-truth labeled.

BERT model

BERT is regarded as state of the art in natural language processing (NLP). The BERT model has been widely used by several researchers since its inception. Authors in Sharevski et al. (2022) explained that the main technological advancement in BERT is the bidirectional transformer training, a standard language model for language modeling. Previously, a text was evaluated sequentially from left to right or right to left, or combined. The profound learning model BERT solves this fine-grained classification challenge (Spiekermann et al., 2015).

On the contrary to directional models that read the text sequentially from right to left or left to right, the entire sequence of words is read at once by the transformer encoder, making it bidirectional. This distinct characteristic enables the BERT model to understand a text's context based on its entire surrounding (right and left of the text). Transformers are multiple layers that contain multiple attention heads. It takes a sequence of vectors h=[h_1,.....h_2] as inputs corresponding to the tokens(n) of the input text. Each vector h_i gets transformed into value vectors and query keys v_i, k_i, q_i by different linear transformations Eqs. (1) and ((2)).

$$a_{ij} = \exp\left(q_i^t k_j\right) \div \sum_{i=1}^{n} \exp\left(q_i^T k_i\right) \tag{1}$$

$$O_i = \sum_{j=1}^{n} a_{ij} v_j \tag{2}$$

Furthermore, the BERT model experimented on several tweets associated with the Jarkata flood (Ningsih & Hadiana, 2021). The Jarkata flood tragedy was a trending issue on Twitter. By analyzing the text tweet, the goal was to find tweets with valuable information on emergency responses to flood disasters. Further experimental results have shown positive results, although; according to them, the data collection's consistency substantially affects the system's efficiency. Authors in Zhou and Zafarani (2020) offer compelling evidence for the importance of incorporating a stochastic gradient descent optimizer for pre-training self-attention language models; it learns to link the text to the aspect and the long-term dependencies using the pre-trained BERT model, and they got an accuracy of 64% (Bandyopadhyay et al., 2014).

Table 1
Review of related literature.

S/N	Authors	Method used / description	Refs. #
1	Kumar and Singh	It uses CNN to extract location words and has F1-score of 0.96.	(Kumar & Singh, 2019)
2	Akerele-Popoola, Azeez, and Adeniyi	Method used: qualitative approach using in-depth interview. Data: 20 Nigerian youths were chosen through snow balling technique.	(Akerele-Popoola et al., 2022)
3	G. D. Haddow and K. S. Haddow	Opens a path to effective disaster communication with emphasis on transparency, increased accessibility, trustworthiness, reliability, and collaboration with the media.	(Haddow & Haddow, 2014)
4	Rathore, Kar, and Ilavarasan	A complete review of the social media analytics (SMA) and directions for future research is discussed.	(Rathore et al., 2017)
5	Chang, Lee, Eltaher, and Lee	Predicting home locations of Twitter users. Compared GMM and MLE. Accuracy of the model is 0.499	(Chang et al., 2012)
6	Middleton, Kordopatis-Zilos, Papadopoulos, and Kompatsiaris	Evaluates five “best-of-class” location extraction algorithms using geoparsing algorithm and a geotagging algorithm F1 score is 0.90+.	(Middleton et al., 2018)
7	McCormick, Lee, Cesare, Shojaie, and Spiro	An accurate and consistent data processing model for social science researchers was developed.	(McCormick et al., 2017)
8	Singh, Dwivedi, Rana, Kumar, and Kapoor	Designed algorithm for flood related area to identify victims asking for help. Prediction accuracy of 87%	(Singh et al., 2019)
9	Song and Huang	Uses sentiment aware model for disaster detection using Tweets	(Song & Huang, 2021)
10	Krishnamurthy, Kapanipathi, Sheth, and Thirunarayan	Wikipedia was used as a basis of knowledge base by exploiting its hyperlink structure.	(Krishnamurthy et al., 2015)
11	Devlin, Chang, Lee, and Toutanova	They introduced new language model called BERT.	(Devlin et al., 2018)
12	Ahn, Son, and Chung	Developed a model related to Ridgecrest earthquake in Southern California from selected organizations (July 2019).	(Ahn et al., 2021)

AdamW optimizer

To further improve the accuracy of the BERT model, we combined it with the AdamW optimizer. The AdamW optimizer is a combination of AdaGrad and stochastic gradient descent, making it an improved version of stochastic gradient descent for training deep learning models. This method is more efficient for working on a large problem that involves large parameters or data. It also saves memory. It works by combining two gradient descent methodologies:

1. Momentum: Momentum: This algorithm accelerates the gradient descent algorithm. This is achieved by considering the exponentially weighted average of the gradients (Eq. (3)).

$$w_{t+1} = W_t - \alpha mt \tag{3}$$

2. Root Mean Square Propagation (RMSP): Root means square propagation takes the exponential moving average and not the cumulative sum of squared gradients in AdaGrad (Eq. (4)).

$$W_{t+1} = W_t - [\alpha/(V_t + \in)^{1/2}] * [\delta L/\delta W_t] \tag{4}$$

Table 1 presents the summary of related research work.

Methodology

This section shows the various methodology put together to achieve the desired goal of our proposed model. Network design is also presented to understand the entire process of our methodology. Method of data collection is discussed first then tool for data analysis and robustness checking is discussed.

Network design

Tweets data are collected via Twitter API and the tweets are cleaned to remove non-English, hashtags, stop words, etc. The network is then built, trained, and tested. A diagrammatic representation of the steps in sequential order shows the network flow diagram (Fig. 1).

Data collection

Tweet collection

Tweet collection can be defined as an editable group of Tweets selected by a Twitter user or programmatically managed through APIs collection (Huang et al., 2019). We collected 10,000 tweets that were related to transportation disasters using disaster keywords such as accidents, fire, and diversion from Twitter streaming API. A sample of the dataset is shown in Fig. 2. The features of the model are transportation disaster keywords (which are determined in the labeling done manually), location, and time. The tweets contain the text tweet, tweet ID, User ID, posting time of tweets, and so on. We kept only the text tweet and eliminated other metadata for the current work. The tweets were divided into 80% training and 20% test data. Training stopped at the 11th Epoch to avoid the model from overfitting. We made use of Google Colab as our work environment and used the Python 3.8 programming language.

Tweet cleaning and preprocessing

First, the tweets were preprocessed to eliminate non-English tweets and then remove redundant tweets. Regular Expression was used to remove hyperlinks, URLs, and punctuation marks. The redundant tweets were further eliminated by finding RT(re-tweets) in the tweet text. Hash tags were further replaced with the corresponding word (such as #accident to accident). The text was transformed to lower case. English stop words were used to remove non-English tweets because of Named Entity Recognition and understanding for Machine learning. Stop words were further retained in the tweet because their occurrence may direct the start of location words. Also, all the words of the whole tweet collection is also kept. The dataset has only the tweet text after pre-processing and user identification marks were removed.

Word embedding

Word Embedding can be described as a kind of word representation which allows for words with similar meaning to be understood by the machine learning (ML) algorithms. It is a language modeling and feature learning technique. There are different word embedding models available, but we used word2vec(Google). Word Embedding helps by providing a way to convert text to a numeric vector. It uses deep learning and neural network-based techniques to convert words into corresponding vectors.

Named entity recognition

Entities can be organizations, people names, times, monetary values, locations, quantities, percentages, and more. In this research, Named entity recognition was needed to be able to extract key information to understand what the tweet was about using these two-step processes:

i. Detection of named entities
ii. Categorization of entities

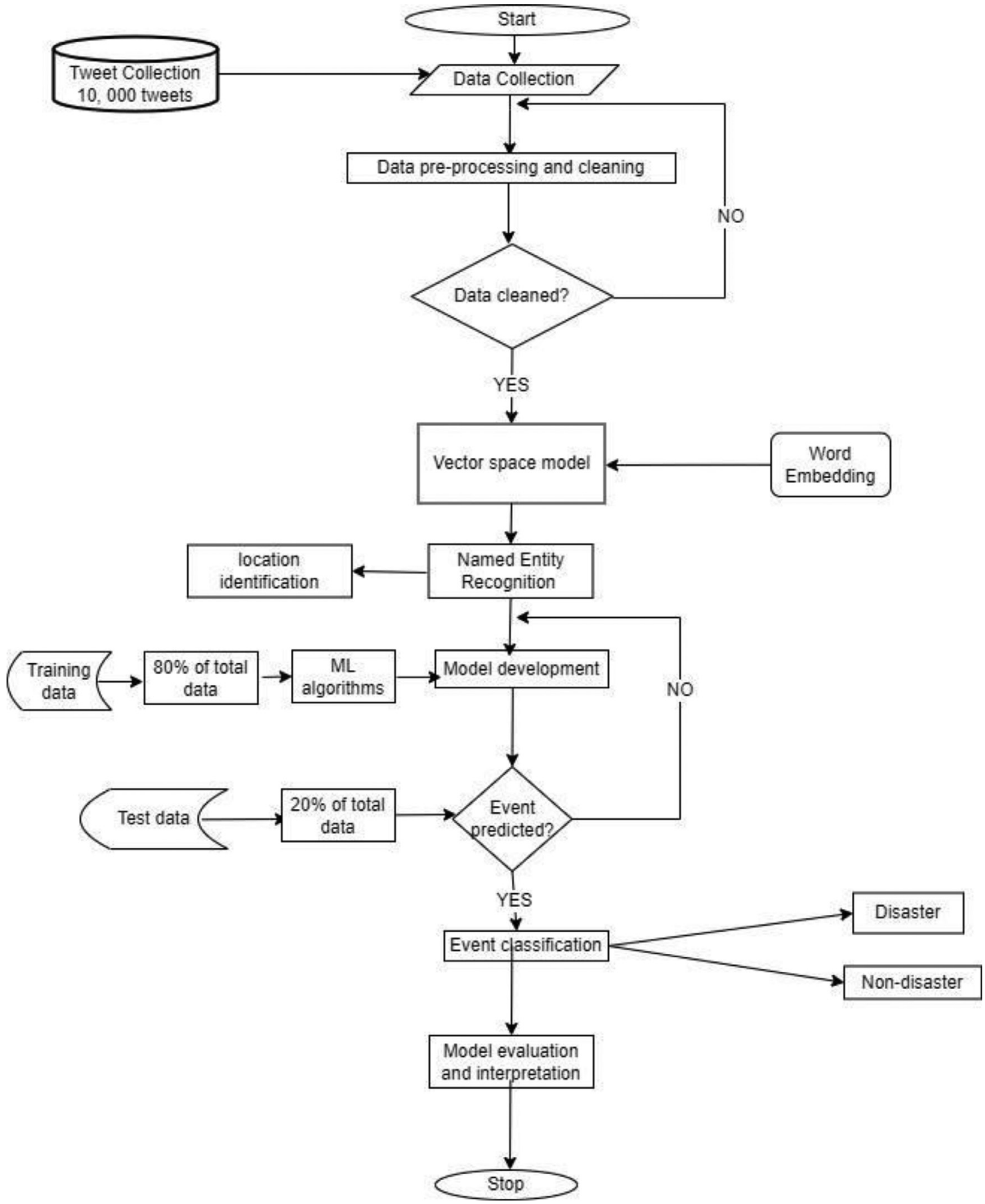

Fig. 1. Network flow diagram.

Detection of named entity: simply the process of detecting a sentence, a string of words or a word that forms an entity. These words represent a token.

Categorization of entity: This involves the formation of entity categories. Some of the entity categories were created for this research.

i. Location – e.g., Abuja, Maraba, Asokoro
ii. Time – e.g. 4pm, 8:00am
iii. Disaster – e.g., accident, a bomb attack

The Named Entity Recognition model trains the data to learn what the disaster tweets are and the non-disaster tweets. The more useful the training data is to the task, the more efficient it will be to complete the task.

Event classification & prediction

Keywords and hashtags in tweet texts make it easy to identify tweets related to an event (Wadud et al., 2022). Though, some tweets may have been referring to a general statement such as "Accidents seems to be a frequent event in Abuja." The tweet in this example refers to accidents that can be a specifically targeted event, but notice it doesn't convey a real-time report of the said event. Therefore, this research develops a machine learning model to group tweets as disaster and non-disaster. Tweets requesting emergency assistance regarding accidents etc. are put in the high disaster category, while general statement tweets such as "FIRS rescues 80 people from Abuja highway" are classified in the low disaster category. We used manual annotation because tweets do not

72	Divert	Whoop Ass, (	Not a diss song. People will take 1 thing and run with it. Smh it's an eye
75	ablaze	Lekki	Rape victim dies as she sets herself ablaze: A 16-year-old girl died of bu
84	Fire		SETTING MYSELF ABLAZE http://t.co/6vMe7P5XhC
87	ablaze	Nyanya	@CTVToronto the bins in front of the field by my house wer set ablaze
88	Rape		#nowplaying Alfons - Ablaze 2015 on Puls Radio #pulsradio http://t.co/
90	ablaze	121 N La Salle	'Burning Rahm': Let's hope City Hall builds a giant wooden mayoral effig
94	ablaze	Asokoro	@PhilippaEilhart @DhuBlath hurt but her eyes ablaze with insulted ang
99	accident	Uniport	Accident cleared in #PaTurnpike on PATP EB between PA-18 and Cranbe
101	accident		Just got to love burning your self on a damn curling wand... I swear som
103	accident		I hate badging shit in accident
106	accident	Ibadan Expre	#3: Car Recorder ZeroEdgeÃ¥Â¨ Dual-lens Car Camera Vehicle Traffic/Dr
108	accident	Massachuset	Coincidence Or #Curse? Still #Unresolved Secrets From Past http://t.co/
111	accident	Nyanya	@Traffic_SouthE @roadpol_east Accident on A27 near Lewes is it Kingst

Fig. 2. Twitter dataset.

have any class information. To train and test the system, this feature is needed. We applied five machine learning classification algorithms for event classification and prediction, namely

i. BERT Model
ii. Support Vector Machine(SVM)
iii. Random Forest Classifier(RF)
iv. Decision Tree(DT)
v. XGBoost Algorithm
vi. Existing work (Hayashi et al., 2016)

Performance evaluation metrics

Performance evaluation metrics are a crucial step to knowing how well a model is performing on test data. This will give you an insight into how well it will work in production. The different performance evaluation techniques used are Accuracy, Confusion Matrix, Precision, Recall, and F1-Score.

Accuracy

Accuracy (Eq. (5)) is how close a given set of measurements are to their true value. It can be described as one important metric when evaluating classification models. It is the fraction of predictions gotten right by the model. Higher the value of accuracy, better the model is.

$$Accuracy = ((TP + TN) \div (TP + TN + FP + FN)) \tag{5}$$

Where TN= True Negatives, FN= False Negatives, TP= True Positives, FP= False Positives.

Precision

Precision (Eq. (6)) is how close the measurements are to each other. Precision is a description of random errors, a measure of statistical variability. Precision (Eq. (6)) can be described as a metric used where the false positive is a concern and not the false negatives. If a model produces no false positives then it has a precision of 1.0.

$$Precision = (TP \div (TP + FP)) \tag{6}$$

Recall

The recall (Eq. (7)) is a metric used where the false-negative trumps the false positive. It shows us how many of the positive cases we predicted correctly with our model. The higher the recall, the more positive samples detected.

$$Recall = TP \div (TP + FN) \tag{7}$$

F1-Score

This is a harmonic mean of recall and precision. F1-Score (Eq. (8)) shows a combined idea of both precision and recall metrics. It is maximum when a recall is equal to the precision. Practically, when we increase the precision of our model, the recall then goes down, and also, when we decrease the precision of our model, it goes up.

$$2 \times ((precision \times recall) \div (precision + recall)) \tag{8}$$

Experimental results

Several experiments were conducted to evaluate the proposed model. This section discussed the different implementations that have been done and the results of these implementations. We collected 10,000 tweets that were related to transportation disasters using disaster keywords such as accidents, fire, and diversion. The features of the model are transportation disaster keywords (which are determined in the labeling done manually), location, and time. The tweets contain the text tweet, tweet ID, User ID, posting time of tweets, and so on. We kept only the text tweet and got rid of other metadata for the current work. The tweets were divided into 80% training and 20% test data. Training stopped at the 11th Epoch to prevent the model from overfitting. We made use of Google Colab as our work environment and used the Python 3.8 programming language.

Classification of transportation disaster

The binary classification was used to determine if the cases were disaster or not disaster (Apuke & Omar, 2021). Fig. 3 shows an example of the classification.

Performance of different classifiers

A comparison of the different performance classifiers is shown in Table 2. The BERT-AdamW model gives higher accuracy, precision, recall, and F1-score than the other classifiers. BERT model uses Transformer that learns contextual relations between words in a text. In a simpler form, Transformer includes two separate mechanisms, a decoder and an encoder that reads the text input. BERT's goal is to generate a language model, therefore, only the encoder mechanism is necessary. To increase its accuracy, AdamW optimizer is integrated into the model.

The model takes a sample tweet "Tonight was Mayhem, Fire outbreak at gudu" this sample text contains the location which is "Gudu", and transportation disaster keyword which is "Fire". The BERT model creates an input id for each of the words and makes them using attention mask and using the pretrained model it correctly predicts the sentiment which is "Disaster". To show the improved accuracy of AdamW optimizer, we also implemented BERT model without AdamW optimizer (Hayashi et al., 2016).

	Unnamed: 0	id	Keyword	Locatiion	Text	Target
0	0	1	accident	Lugbe	There is an #accident right now in #lugbe expr...	1
1	1	4	NaN	NaN	No road to pass oh! Tunde you don see	0
2	2	6	diversion	NaN	Lekki is #closed, kindly apply #diversion	1
3	3	9	Injury	Lekki	There is flow of blood in this #endsars in #le...	1
4	4	12	NaN	NaN	Burnaboy is better than Davido, argue with you...	0

Fig. 3. Classification of tweets into disaster and non-disaster.

Table 2
Comparison table for the performance of different classifiers.

S/N	CLASSIFIERS	ACCURACY(%)	PRECISION(%)	RECALL(%)	F1-SCORE(%)
1	Proposed model- (BERT-AdamW)	0.82	0.83	0.86	0.84
2	SVM	0.81	0.81	0.90	0.85
3	RF	0.78	0.78	0.89	0.83
4	XGBoost	0.78	0.79	0.87	0.83
5	DT	0.67	0.73	0.71	0.72
6	BERT-Existing work (Hayashi et al., 2016)	0.64	0.61	0.78	0.74

Discussion

This research proposed a model to reduce transportation accident emergencies in Nigeria by identifying tweets in real-time using Twitter API location and further detecting and classifying the severity of the accident. Since GPS gets disabled by many Twitter users in Nigeria (intentionally or unintentionally), retrieving the location of tweets and user is a challenging task. This research proposed an alternative to GPS called Named Entity Recognition (NER) to identify transportation disaster location by analyzing the tweet text alongside the location database.

This research improves the accuracy of BERT model by integrating AdamW optimizer within it. Table 2 shows that the proposed model has better accuracy than the existing BERT model. Improvement is due to the fact that the AdamW optimizer is a combination of AdaGrad and stochastic gradient descent, making it an improved version of stochastic gradient descent for training deep learning models. Apart from improving accuracy of the BERT, our model is more efficient for working on a large problem that involves large parameters or data. It also saves memory. From Table 2, accuracy of the four other classifiers (SVM, RF, XGBoost, and DT) is recorded as 81%, 78%, 78%, and 67% respectively. Support Vector Machine (SVM) has good accuracy over here but it is not recommended as it is not suitable for large data sets; we have the intension of increasing the size of dataset in the near future. Random forest (RF) has good accuracy but main limitation of this is: it becomes slow due to large number of trees and hence becomes ineffective for real-time predictions like disaster. Though accuracy of XGBoost algorithm is good but it does not perform so well on sparse and unstructured data (like Twitter dataset). Decision tree is not recommended for this study due to its low accuracy.

Proposed model is behaving well in the case of unstructured dataset as compared to other model in the literature. Our model will contribute immensely in providing valuable information to first responders Government agencies and even individuals who ply the roads being affected.

Contributions to literature and implications for practice

The identification and classification of transportation disaster using Twitter API developed in Python Programming language using a combination of BERT model and Adamw optimizer will contribute immensely in providing valuable information to first responders Government agencies and even individuals who ply the roads being affected. It can also serve as a building block for multi-classification which will also further improve in not just providing information but being able to help the first responder's Government agencies to dispense appropriate tools and man power based on the level of disaster.

Future work

The following are the opportunities for further research:

i. Get more data to get higher accuracy with the BERT model.
ii. Further dissect the “disaster” option to be able to detect the level of disaster, which will enable the response Agency to know what to expect before going to the field.
iii. Consider other classification algorithms and pay attention to accuracy.
iv. Develop a multiple classification transportation disaster model, carry out an accurate survey and compare to the ones in this research. This might provide results more suitable for prompt disaster detection.
v. Discuss the effect of data dynamics on our proposed model.

Limitation of the study

This research has only used the binary classification approach for the classification of disasters. There are other approaches for classification, such as the multi-classification approach, which is not considered in this study. This paper is limited by the fact that the location of the transportation disaster is received through Named Entity Recognition. Therefore, if a user does not indicate their location, we cannot determine the location of the transportation disaster.

Conclusion

Nowadays, Social Media is becoming most sought-after means of getting evidence and dispersing information by both the government agencies and individuals, especially after its unique part in the just concluded #endsars protest and the ongoing COVID-19 lockdown phase in Nigeria. Twitter is ranked the number one most used social media platform in Nigeria, making it a better choice for data collection. There are different research on disaster detection and classification using the algorithms: SVM, RF, and DT. Contrary to directional models, the BERT reads the entire sequence of words at once.

Experimentation is performed using the Twitter dataset alongside the use of evaluation parameters of recall, precision, accuracy, and F1-score. From the evaluated results, it can be declared that the proposed

BERT Model with a combination of AdamW optimizers outperformed in comparison with SVM, RF, and DT.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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