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An Autoregressive Transformer Model For Crisis Management Using Twitter Tweets

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Abstract

A disaster is a major event that lasts for a long time and causes a lot of damage to people, property, the economy, or the environment. The damage is so bad that the group or society that is affected can't handle it on its own. When a disaster happens, it costs developing countries the most. More than 95% of all deaths from hazards happen in developing countries, and as a share of gross domestic product, losses from natural hazards are 20 times higher in developing countries than in developed nations. To minimize the loss at the time of disaster and to overcome it quickly, a survey is taken on how to manage disaster effectively using Machine Learning and social networks. Social media platforms like Twitter, Instagram and Facebook acts as a communication medium during disaster and also help to take preventive measures before the occurrence of the disaster. Machine learning algorithms also helps in response and recovery phase after the occurrence of the disaster. The paper aims to provides an elaborated review on the concepts of Machine Learning (ML) along with social media and addresses how various other technologies like use of physical sensors, Remote sensors, Graphical Information System (GIS), Internet of Things (IoT) and Neural Network[†]s like Artificial Neural Network (ANN), Deep Neural Network (DNN) can combine with Machine Learning algorithms for the management of disaster efficiently using social media. Finally, based on the study, a generalized autoregressive pre-training method called XLNet is proposed which overcomes the limitations of BERT using its autoregressive formulation and directions for the future research is explained further.

Keywords: *Machine Learning (ML); Deep Learning (DL); Classification; Neural Networks; Graphical Information System (GIS); XLNet.*

1. Introduction

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For the past several years, the urge for the management of disaster has been increasing tremendously [6]. The disaster occurs in either of the two ways, one is man-made disaster and the other one is natural. As we all know that the term disaster denotes a serious problem which occurs for a short or even may be for a long period of time. As a result, it leads to losses like death loss, economical loss, and environmental loss and so on. So, considering the seriousness, the disaster has to be either stopped before the occurrence which is not possible for natural disasters or should be able to get recovered from the disaster immediately after the occurrence of the events [11]. For both the cases, timely detection of disaster, providing accurate information about the event [9], effective communication for the management of disaster and taking immediate action for reducing the severity and seriousness of the disaster are required. Till date, people are suffering a lot due to lack of proper management of disaster [1]. It occurs mainly due to lack of proper communication [24] before and after the disaster. During the time of disaster event, all the modes of communication in the affected area could be down which is very difficult and becomes highly challenging for those people to get recover from that particular disaster [29]. To overcome the mentioned problems, several steps are required and they are,

1. Designing an alert warning system before the occurrence of the disaster [9].
2. Implementing Emergency communication system for the timely relief, response and mitigation purpose [4][25].
3. Providing accurate and vital information to the people from surrounding area [15][17].
4. Creating a GIS based system for finding out the location of a particular disaster event [11].

The methods to be developed for the management of disaster should be robust enough to handle the challenges affecting the disaster management system. Several technologies were emerging for the effective management of disaster. The emerging technologies are Artificial Intelligence with the subset of Machine Learning which again with the subset of Deep Learning and Neural Network [6], Sensor based methods [13], Remote sensing technologies, big data-based methods [14], satellite-based technologies for tracking the location [22] and Internet of Things (IoT) [23]. Among all these methods, Machine Learning and its subset plays a vital role in day-to-day life as it becomes one of the mostly used successful key computing technologies. The other methods didn’t achieve successful state because in those methods, the network becomes more autonomous and these methods require multiple local decisions to be made like selection of bandwidth range, selection of data rate, power control, fixing of sensors and availability of data from the database which are the major drawback and requires man-power for those methods [5][8]. So, instead of using these methods, optimum Machine Learning algorithms can be used to address the above problems and data can be taken from online social networks like Twitter [3], Facebook, Instagram [7], YouTube and so on. To conclude, Machine Learning (ML) algorithms have advantages like,

1. ML algorithms help in processing huge volume of data. As data increases, the performance also increases which results in producing highly efficient results.
2. ML algorithms provide optimum results. It helps in making decisions quickly and reduces the human intervention [29].

3. It helps to handle multidimensional data and makes fast and reliable decisions.

In addition to these benefits, the results obtained after the classification reaches high accuracy. Classification is done with the help of training and testing the data from the dataset [1]. The overview of the paper is organized as follows. Section 1 provides Introduction about the paper. Section 2 provides a short summary on ML and Social networks. Section 3 discusses about recently reviewed papers related to disaster management using ML and DL applications. Section 4 discusses about recently reviewed papers related to disaster management using social media. Section 5 presents other emerging technologies and its applications. Section 6 represents a proposed idea based on the survey done. Section 7 provides open issues and challenges in existing methods. Last section 8 presents conclusion and future work for the paper.

2. Study on Machine Learning with the effect on social media

2.1. Overview of Machine Learning

This section discusses about the study made on one of the top emerging successful and trending technology, Machine Learning. It also presents various ML algorithms which are used for the management of disaster. The origin of ML came from Artificial Intelligence (AI) [14]. AI's major objective is to make the machine of any kind to think and act like a human being. The decisions which are taken by the machine should be similar to the characteristics and thinking of human behavior. For example, AI makes the machine to solve complex problems like the human used to do. Whereas ML is a subset of AI as shown in figure 1 which helps the machine to take decisions and solve complex problems based on the training and testing of data.

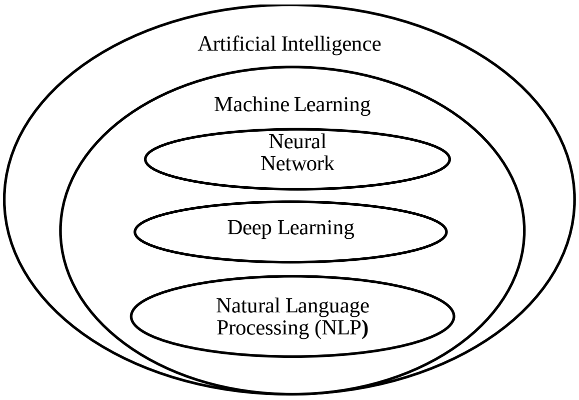

Fig. 1. Artificial Intelligence and its subsets

Now, coming to ML, it works on algorithms which learn by its own using historical data. ML can be categorized into 3 types, i) Supervised Learning, ii) Unsupervised Learning and iii) Reinforcement Learning. The overview of types of ML is explained below.

2.1.1 Supervised Learning:

In this type, labeled data is used for training the machines, which helps them to predict the output easily and accurately. If there are some errors in the labeled data, then the efficiency and performance of the system gets affected. The output is predicted based on the test data provided. The working of supervised machine learning is shown in figure 2.

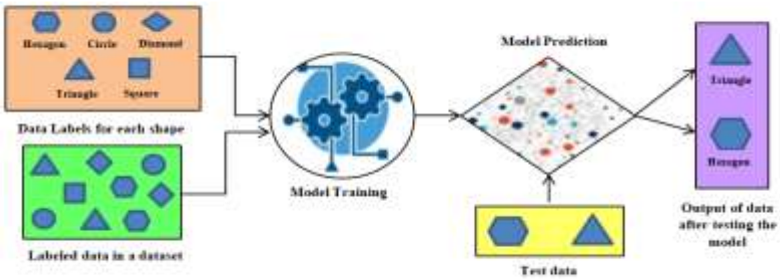

Fig. 2. Working of Supervised Learning Model

Supervised learning is further divided into two categories. One is Regression and the other one is Classification. Regression uses some algorithms like linear regression, Non-linear regression, polynomial regression and Bayesian regression in predicting applications like weather forecasting, marketing trends and so on. Whereas, classification is used when we can categorize the output variable to Yes-No or to Male-Female or like True-False etc. It uses algorithms like Decision Tree, Random Forest, Support Vector Machine (SVM), Logistic Regression and Naïve Bayes for the classification of objects, texts, images and so on. The major advantage of using supervised learning is that it helps to solve real-world problems like fraud detection, fake news detection, spam filtering [50] and so on. But supervised learning model cannot handle complex tasks.

2.2.2. Unsupervised Learning:

Here, unlabeled data is used for training which allows the machine to solve complex problems without any supervision. In other terms, we can tell that, unsupervised learning works by finding the underlying structure of the data used for training. The underlying structure is found out by grouping the data based on the similarities of those data [23]. The working of unsupervised learning is shown in figure 3.

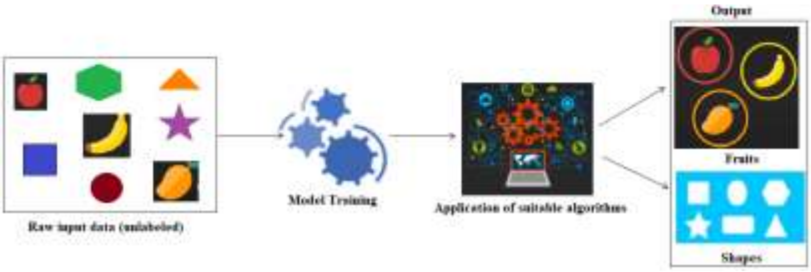

Fig. 3. Working of Unsupervised Learning Model

Unsupervised learning is further classified into two categories. One is Clustering and the other one is Association. Clustering groups the data from the dataset based on their similarities [46]. It categorizes the data objects based on the presence and absence of its commodities; whereas, association is a rule-based model which finds the relationship between each variable in the dataset. It is mainly used in the field of marketing. Some algorithms used by unsupervised learning model for clustering and association are K-Means clustering algorithm, K-Nearest Neighbor (KNN) algorithm, Anomaly detection, Neural Networks, Principal Component Analysis (PCA), Independent Component Analysis and Hierarchical clustering algorithm. The basic advantage of using unsupervised learning algorithm is that it helps to handle high complex problems. But the major drawback is, the output obtained from unsupervised learning may not be accurate enough like the supervised learning model as the data are unlabeled.

2.2.3. Reinforcement Learning:

It is a feedback-based technique of ML. In this model, instead of labeled and unlabeled data, agent plays an active role. Here, agent learns to behave like a human by performing actions and observing the results of those actions. The working of reinforcement learning takes place by an agent. If the agent receives positive feedback or rewards, then the agent gets positive point. If he gets negative feedback or penalty, then he earns a negative point. So, agent aims to earn a positive point which denotes that the output is positive (success) else the output is denoted as negative (failure). Reinforcement learning is used only when the data is not sufficient for training. The drawback in this model is, if the feedback received is delayed, then the speed of the learning gets affected thereby affects the performance of the system. The working of reinforcement learning model is shown in figure 4.

Fig.4. Working of Reinforcement Learning Model

2.2. Study on Social Networks & Micro Blog

Social Network originated from the term social media, is a computer-based technology which helps people to share their own ideas, thoughts and any kind of information via a virtual network [10]. It also helps people to communicate with one another quickly and easily by sharing one's personal information like photos, any kind of documents and even one can upload videos. As per the recent survey taken from all over the world, the total number of people who use social media are more than 4.5 billion users. Social media helps people to connect simultaneously with their families and friends from anywhere easily and has shorten the distance between them [17]. The main reason of using social media is, it helps to build relationships with families, friends and business people and also help to connect with the customer and server [28]. It provides a space to share our own thoughts. In addition, we can collect number of information that happens in our day-to-day life via social media. It also acts as a faster communication medium as large number of users are active in social media. It helps to connect people easily from anywhere and at any time thereby reduces the distance between them. Social media acts as a bridge to find career opportunities across the globe [48]. Social media can be categorized into several types. But among all types, social networks like Twitter, Facebook, Instagram and LinkedIn) are considered as the world's largest social media networks [9]. As days goes on, the growth and usage of social media increases tremendously and acts as a platform to share information, opinion and their thoughts regarding any social events. Figure 5 shows the different types of social media.

Fig. 5. Types of social media

During an emergency situation, in order to save lives of people, quick decisions are needed to be taken [25]. So, considering the scenario, social networks are used which acts as an abundant source with up-to-date data and useful information generated by users. The use of social networks during natural disaster is proposed in 3 ways. They are,

- Preparation – No one can predict any kind of natural disaster in advance. With the help of email, text messages and posts, people can prepare themselves and make others to prepare as well during the time of emergency situation. This stage helps in sharing emergency information for any kind of disaster events very quickly [26],
- Response – During and immediately after the occurrence of the disaster, users of social media co-ordinate with the rescue team and activities as the users continuously update the critical information during the event [12].
- Recovery – After the occurrence of the disaster, with the help of social helpers and rescuers, it is necessary to get recovered from the event quickly and immediately to reduce the losses like death, economic loss, environmental and material losses. So, social media serves as a communication channel which is highly valuable by offering assistance and help at the time of disaster [37].

These are the 3 important stages used to manage the disaster effectively with the help of social media. This unique role of social network attracts several people from the department of blue cross, telecommunication organization and even transportation department to continuously monitor the posts in social networks which helps them to take appropriate and timely actions to reduce the impact of the disaster. Among all social Medias, Micro blog plays a major part as it allows users to share a short message to its internet community. Among several micro blog services, twitter is considered as its main component because in the last few years, the urge to use twitter increases tremendously all over the world. [49] During an emergency situation, people post large number of useful information via twitter including their thoughts and opinions along with their sympathies. Therefore, twitter is considered as a reliable platform for extracting the useful information.

3. Overview of Existing Models

This section provides a short description on existing models and technologies along with their drawbacks.

Zhicong et al [33] proposed a multi-stage event detection model to describe global and local hot events. Firstly, a community detection method is used to divide the users into different communities. Then the user related graph is constructed and agglomerative algorithm is used to find the communities on that graph. Before using LDA model for topic modeling, NLPIR is used to conduct segmentation of Chinese words and then the parameters are set for performing topic modeling using LDA algorithm. It clusters the topics from tweets collected. Finally, text classification algorithms are used to classify local and global hot events and precision, recall, F-score has been calculated. The drawback in this work is that LDA topic modeling does not reduce redundancy and the results were not accurate. Social media gives voice to people who do not have one normally. It remarkably helps public to address any kind of event and exchanges the information according to their opinions. Social media stimulates the tendency of public to coalesce their views during an emergency situation or to induce donations for the event occurred. Even though it has some ethical issues like stalking, stimulating racism, threats of violence and criminal activities, social network plays a major role in disaster reduction and response. In Japan, during Tsunami and Earthquake happened on March 2011, social media played a dreadful role in locating missing people, facilitating public alerts and enabled mapping function for the emergency situation. Several examples [34] can be given for listing the benefits of social media.

Sumalatha et al [35] proposed a GDSS model, which provides immediate relief after the occurrence of the disaster event. Geo Distributed Service System (GDSS) uses social media like Twitter and Facebook as a platform to reach people for help during such emergency conditions. In this, a dedicated web service is created and a picture of the disaster event occurred has to be uploaded using mobile in social media to the web service. The web service collects the data of nearest relief center from Cassandra database and inform them about the disaster event happened to provide immediate service and appropriate recovery measures. The web service calculates the coordinates (latitudes & longitude) from the picture posted and share the location to relief center to reach the location on time and to provide the needy help. Figure 6 shows the GDSS system for emergency distress relief from disaster using social networking platform.

Fig. 6. GDSS System for disaster recovery

The drawback with this proposed system is that it requires a lot of manual help from the coordinator which may lead to human error and loss of data. A natural disaster analysis interface method is proposed in [39] in which tweets are captured using tweet streaming API which captures live tweets from the web and then redundancy checking is done to remove the repeated tweets. Followed by that, the redundancy free tweets are stored in the database for data sorting. During data sorting the type of disasters (Earthquake, Flood, Drought and Forest fire) are filtered and clustered using KNN algorithm. Once it is done, analysis and interpretation take place on the clustered data. Under that, geo-tagging, disaster distribution analysis, disaster occurrence frequency and users' emotions are analyzed. Thus, the emotional state of the user is visualized during the disaster event using tweets. To decrease the negative impacts on natural crisis like Earthquake, Flood, Drought and Forest fire, it is essential to reach the degraded areas accurately on time. For that, geospatial information is foremost required to reach the exact place. To achieve the goal, a modern DeepEye structure is proposed [49] in which Convolutional Neural Network (CNN) is used to quickly diagnose and automatically discernment from Unmanned Aerial vehicles (UAVs) images in order to calculate the exact locations along with the degraded areas percentage.

Makker in [40] proposed a solution to manage the disaster efficiently by making use of satellite images and social media data to aid disaster response agencies. The proposed system traces usable roads in flooded regions and categorizes areas based on satellite images and find out the roads which are not affected and where people could be grounded. To trace the usable roads, maximum number of pixels connected concept is used. To differentiate regions based on the damage extent, pre and post disaster satellite images are used. Based on some specific keywords, Twitter data was filtered to analyze the needed items and identify the stranded people's locations. Paper [44] proposed a disaster management method where input is taken from social media images and stored them in a database and outputs the category of images using machine learning algorithm which helps the emergency responders to act quickly. Next image filtering is done in which relevant and duplicate images are checked and removed. Relevancy checking is done using CNN and duplicate images are found out using perceptual hashing technique. Followed by that manual labelling is done and finally classification is done on different categories like affected people, affected areas, rescue and damaged infrastructure. The figure 7 shows the

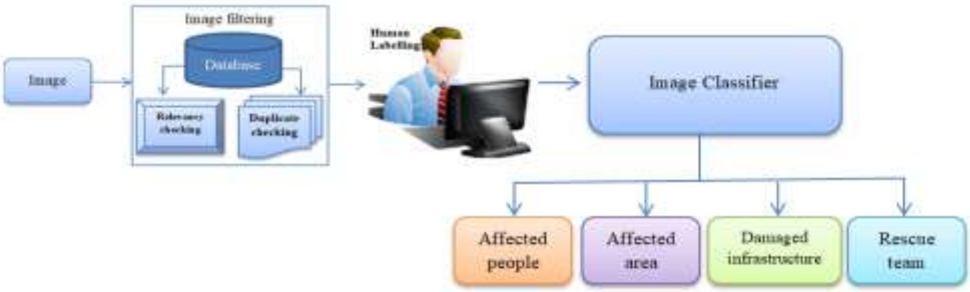

Fig. 7. Workflow of Image processing

working of the proposed model [44].

Paper [45] proposed a model to perform sentimental analysis on collected real time twitter data. McDonald’s and KFC tweets are extracted using twitter API and cleaning is done using pre-processing. The model classifies each and every tweet based on positive, negative and neutral tweets to highlight the popularity of the restaurant. Several Machine learning algorithms like naïve bays, decision tree, random forest, SVM, bagging and maxtent are tried and their metrics like precision, recall, F1 score and cross validatory score are calculated to show the popularity. Among both the restaurants, KFC achieves the highest popularity score of 78%. Along with the above methods, some other techniques which are used to predict the disaster are shown in table 1. The table covers information like methodology or technique used, focus of issue, hardware's or API used along with the category.

Table 1. Summary of different methodologies used so far

Category	**Target issue**	**Methodology used**	**Dataset/Hardware/API used**	**Year**
Big data	Critical information classification	Classifier chain	Twitter API	2022
Open data	Data management to Korean flood disaster	Cross-domain Knowledge graph	Korean open dataset	2021
Graph theory	Disaster recovery management	Pandemic graphs' Chromatic core sub-graph	None	2021
Deep learning	Disaster management	LSTM, VGG13 and VGG16	MNIST dataset	2021
Machine Learning	Emergency response & coordination after disaster	Naïve bays, SVM, LDA from topic modelling	None	2021
NLP & Machine Learning	Block-chain Based Event Detection and Trust Verification	CNN, LSTM and Block-chain	Google & Microsoft API	2022
Deep learning	Disaster response process	Deep learning auto-encoder, CNN, GIS	OSM Overpass Turbo API	2020
IOT & ML	Prediction of flood	CNN	Hadoop map reduce	2020
	Prediction of rain	ANN & Logistic regression	Lorawan	2019
ML	Evacuation route Determination	K-medoids and	None	2019

		Reinforcement learning		
		Deep neural networks	Raspberry Pi	
	Crowd Classification	CNN and k-means	None	
Social media	Predicting people who can come back after death	Gradient Boosting	Twitter data	2019
	Identifying useful tweets	Logistic Regression & Naïve Bayes		
	Relation of tweets between disaster affected people with non-affected one	Dirichlet regression & Dynamic Query Expansion (DQE)		

4. Proposed Model

From the previous State of Art analysis, we can observe that Disaster Scenario environment problems are mostly encountered using machine learning and deep learning algorithms. The proposed disaster prediction model from tweets can be done using Natural Language Processing which is the best suited method to predict the disaster. After analysing several machine learning classifiers, an autoregressive transformer model "Xlneter" is proposed which helps to predict the disaster quickly and efficiently with accurate results. The model combines the functionalities of BERT Topic and XLNET as they provide efficient results when embedded. The reason why XLNET, a pre-trained model [51] is preferred over other classification algorithm is (1) Permutation-based training: XLNet uses the "Transformer-XL" architecture to train permutations, unlike BERT and GPT, which use left-to-right or masked language modeling objectives. (2) Autoregressive and autoencoding: XLNet trains with autoregressive and autoencoding objectives to capture bidirectional context and word dependencies. (3) No pretraining task restriction: BERT and GPT are pretrained on masked language modeling and sequence estimation. Instead, XLNet is trained on a variety of activities using an unsupervised aim to capture more language features. (4) Relative positional encoding: XLNet employs a novel "relative positional encoding," which records token distances in a sequence. This helps to model long-term dependencies better than others. The step-by-step procedure to execute the proposed method is explained below.

1: Twitter Tweets are collected and given as input for pre-processing.

2: Using tokenization, lemmatization and stop words, the data is pre-processed.

3: The pre-processed noise free data is fed as input to the BERT topic modeling algorithm. It clusters the words into several group of topics which makes a way to predict the disaster type efficiently.
4: The output from BERT Topic is given as input to XLNet for training and then testing takes place. 3 kinds of embeddings (word, token & segment) have been set and parameters are modified with our own data so that it can perform better on our NLP downstream task.
5: After training the model, evaluation takes place to know how well the proposed model works. At this stage, several metrics like Precision, Recall, F1-Score and accuracy are calculated to prove the efficiency of the model.

Working of XLNet:

The architecture of the proposed work “xlneter” is shown in figure 8 and explained below.

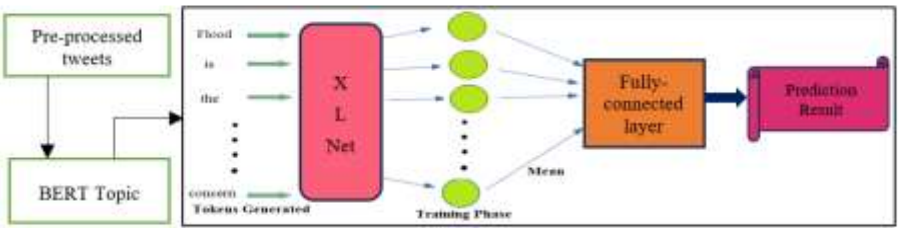

Fig. 8. Architecture of XLNet

The architecture of the XLNet model is derived from the transformer architecture, featuring multiple layers of multi-head self-attention and feedforward neural networks. The structure of XLNet can be decomposed into the subsequent operations:

- Input Encoding: The text that is input undergoes a process of tokenization, wherein it is divided into subwords. Additionally, positional embeddings are incorporated into each token so that they accurately convey the sequential order of the text.
- Permutation is used to randomize the input sequence, hence eliminating the dependence on left-to-right context.
- Transformer Layers: The permuted input sequence undergoes a sequence of transformer layers, wherein each layer comprises self-attention and feed-forward sub-layers. The result of one of the transformer layers undergoes a reverse permutation layer in order to reinstate the initial order of the sequence.
- Output Prediction: The subsequent token in the sequence is predicted by using the ultimate concealed states of the transformer layers, akin to conventional language models.

Even though the model attains the state-of-the-art method, the choice of hyperparameters had a major impact on the performance of the model. In the proposed model, the hyperparameters are adjusted as follows to gain an effective result.

- Number of hidden layers: 24 (default)
- Number of attention heads: 16
- Dropout probability: 0.1
- Learning rate: 0.0001

Based on the altered parameters, the model is trained for 4 epochs and achieved an accuracy of 81%.

5. Results and Discussion

XLNet employs Transformer XL as feature extraction architecture, which is superior to BERT's Transformer due to the addition of recurrence to the Transformer. As a result, the XLNet will have a better understanding of the language context. The first step of xlnet is to pre-train the model. Once it is done, fine-tuning of parameters takes place to update the pre-trained model to fit downstream task needed. The classification of text using XLNet is accomplished through the following four stages. (1) Loading the pre-processed data, (2) Set data into training embeddings, (3) Train and test the model using classifiers, and (4) Evaluate the model performance using metrics. A comparative study of several classifiers has been made and XLNet integrates state-of-the-art work in natural language processing with novel strategic decisions in tackling the language modelling challenge. The model achieves state-of-the-art performance on the usual NLP tasks when trained on a large NLP corpus. Table 2 shows the analyses of different classification algorithm along with the metrics calculated. Among several classifiers, XLNet provides efficient result compared to other algorithms and hence considered as the best method to predict the crisis.

Table 2. Calculated metrics for each model

Model	**Accuracy (%)**	**F1-score**	**Recall score**	**Precision score**	**Mean square Error**	**Mean absolute error**
Naïve Bayes	72.58	0.723	0.742	0.730	0.274	0.274
Random Forest	80.01	0.789	0.794	0.786	0.202	0.202
Decision Tree	77.88	0.768	0.769	0.767	0.221	0.221
LSTM	80.36	0.799	0.800	0.799	0.196	0.196
Xlnet	**81**	**0.806**	**0.814**	**0.804**	**0.190**	**0.190**

6. Conclusion

In order to function effectively during the crisis and utilize the available resources to their fullest, the proposed autoregressive model attains an effective solution by achieving the accuracy of 81% when compared with other algorithms like naïve bayes, decision tree, random forest and Long Short-Term Memory (LSTM). This article also provided a thorough overview on the uses of ML in pandemic and catastrophe management. The study paves a way to understand more about the existing technologies and their uses for further research. The future work is to use geo-spatial information and geo-locators to predict and to provide quick relief from the damages caused after the disaster.

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