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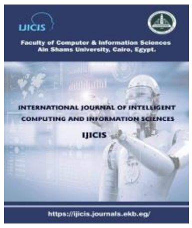

QUESTION ANSWERING TECHNIQUES FOR DETECTING NEEDS OF PEOPLE IN CRISIS

Esraa Karam*
Informatiom Systems Department, Faculty of Computer and Information Science, Ain Shams University, Cairo, Egypt
esraa.ahmed.std@cis.asu.edu.eg

Wedad Hussein
Information Systems Department, Faculty of Computer and Information Science, Ain Shams University, Cairo, Egypt
Wedad.hussein@cis.asu.edu.eg

Tarek F. Gharib
Information Systems Department, Faculty of Computer and Information Science, Ain Shams University, Cairo, Egypt
tfgharib@cis.asu.edu.eg

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Abstract:*The use of social networks has become one of the basics of daily life to follow the news, and also in the case of inquiries and requesting assistance***.** *In case of a crisis, information about the event begins to spread on social networks with the aim of raising awareness and knowing all the important instructions and requesting assistance. This information can be used to respond to people with the required needs depending on the type of assistance or inquiry requested. In this paper, an approach was proposed that uses Question Answering techniques based on natural language techniques and neural networks to extract the needs of affected people during a crisis and provide the proper response. The approach was tested on twitter data from different types of crises. The results showed that the suggested approach can answer with suitable guidelines with a precision of 0.81, a recall of 0.76 and an f-score of 0.78.*

Keywords:*Question answering, Text analysis, , machine learning, word embedding, Neural Networks.*

* Corresponding author: Esraa Karam
Information Systems Department, Faculty of Computer and Information Science, Ain Shams University, Cairo, Egypt
E-mail address: esraa.ahmed.std@cis.asu.edu.eg

1. Introduction

Recently, social networking sites have spread among users. Circulation of official and basic news on it began as a means of disseminating important information, and many users began to follow all events and their development through social media, and also to request assistance in cases of emergency.
During a disaster event, there are various information about crisis which are considered as different categories or event types such as "reports of injured, trapped, or deceased people", "urgent needs of victims", and "infrastructure damage reports", are required by humanitarian organizations for the planning of relief operations. Microblogging platforms such as Twitter are used to spread this information by the affected people. Therefore. social media are useful in this time-pressing situation, but it is challenging to analyze and extract useful information from large amounts of crisis-related data available on social media.[1]
During the time of disasters, the use of social media increases significantly because people are trying to reach their family and friends and enquire about their safety. Therefore, lots of people start sharing information about food and shelter and about all the help that can be provided, and people start interacting to help. The use of social media among people increased during the occurrence of crises because in many violent crises, such as earthquakes or floods, most traditional communication methods such as mobile networks are cut off. Therefore, many organizations have begun to focus on the assistance required through social media and how to respond to the required need.[2]
Most of the research in the field of crisis management has taken the path of discovering people’s needs that were published on social media during the state of emergency. As this process depended, in the beginning, on extracting keywords such as food or shelter, through which the type of aid needed could be determined. Then text analysis and classification techniques are used to classify all data according to the appropriate type of requests. Also, the focus began on trying to understand the content of the text to extract the demand. All these techniques are applied on one type of crisis to understand the major keywords about the crisis and extract the related information about crisis, its damages and its related needs. In this paper, we aim to detect the needs of affected people in twitter in various crises by using question answering techniques depending on deep learning and neural networks to understand the content in the text and reply with the useful answer.
The rest of this paper is organized as follows: section 2 presents a review of the research done in the fields of crisis detection in social media, the proposed method is explained in section 3, the experimental results are presented in section 4 and finally, section 5 provides the conclusion.

2. Related Work

Social media became the main portal where one can follow all important news and events are launched quickly. Therefore, people began to use social media, specifically Twitter, during a crisis as can be seen in the literature in the period of 2007–2019. So, there are many researches that cover the techniques and methodologies related to the use of social media data in crisis management field [2].
Therefore, research began to focus on detecting major public events using tweets. The work in [3] proposed a system named "Twevent" which is used to achieve this goal. The proposed pipeline for event detection follows a set of steps: (1) the tweets are separated into a set of segments and a weighting

scheme is used to rank them. (2) Only the top K segments are used in clustering to obtain the candidate event clusters only those related to real world events of interest.
A process for event extraction was developed in [7] by applying a new paradigm which formulates as a question answering (QA) task based on machine learning techniques and neural network algorithms. The approach takes the user's sentences as input context data which the information is extracted from, and uses standard questions for each arguments of event as templates like "Who is the agent?", "Where the event takes place?". So the arguments of events could be extracted in an end-to-end manner. So, it can extract arguments for new events not seen at training step.
During any crisis, a large number of tweets are created, including news about the crisis, a request for assistance, or a follow-up of the development of events, but there are also many news that are not related to the crisis. Therefore, it is necessary to try to filter this amount of data to try to access information related to the crisis only and quickly by using different Machine Learning (ML) techniques to classify related tweets from non related.[6].
Furthermore, the research challenge is to extract the important events, also called "event types" or "categories", and to identify their sub events by considering their locations and semantic relationships within a major event type from social media data. The process of detecting an event's type and its sub events provide an understanding of all events associated with a disaster as well as the relationships among co-occurring events by using two clustering algorithms for major and sub event extractions [4].
Also, extracting the public information during events such as disasters and track their evolution on social media are depending on 3 levels for topic analysis : global level , sub-topic level and detect themes for each sub-topic level. The results are interpreted into information related to public demand by applying an interactive method combining topic-modeling with manual interpretation, and interaction is used to detect the information requirements of the public [8].
The field of research in crises began to focus on all the information produced in times of crisis, not only determining the type of crisis, but also the results related to it. Therefore, the large amount of social media posts are considered a useful data source to recognize people's mental health during a period of the crisis such as COVID-19 by analyzing the popular topics and their associated sentiments due to the crisis[5].
All research in the field of crises has the main goal of knowing the type of crisis, reaching the injured, and knowing all the required needs. Since social media is one of the most important means of spreading news, it has also been used to request assistance to speed the spread of information. Research has begun in the direction of also revealing the needs of the people affected in crisis by creating a Crisis Message Corpus from geotagged tweets. Using this corpus to train a classifier that identifies help requests in real time [9], using a semi-automated artificial intelligence-based classifier to classify the tweets into categories like "community needs", "loss of lives", "damage" [10][13] then detect the key features for each type of situational information by extract 5 groups of features (emotional ,perception , Affiliation-related factors ,user -related factors , and Content-related factors) [15] , or using a dense classifier with contextual representations (Embeddings from language models) which is considered as more accurate classifier than traditional classifiers [11].
During crisis, not only affected people wrote for help also the people who can help and give any available to affected people. Therefore, A semi-automated platform called NARMADA is proposed to collect all social media posts which include all information about assisting post-disaster relief coordination efforts by applying Natural Language Processing and Information Retrieval techniques for detecting the needs and the available need-related resources to match the needs and its suitable resource [12], or detect the needs from social media but using the resources from the official organization and agent like World Health Organization's (WHO) in case of COVID-19 which provide resource planning

guidelines by proposing two methods for 2 distinct but related needs detection tasks (1)detect the top needs for COVID19 by using word embedding to obtain the closest terms to needs and supplies(2) Specific needs detection to identify people who needs particular resource by using rule-based methodology [14].

Most of previous related work focus for detecting other details related to crisis not only the type of crisis but also the related sub events and the needs of affected people which is the major purpose in the crisis management process. Trying to handle the emergency situations to help the affected people. the researches focused on detecting the needs by trying to extract the keywords belongs to needs from their tweets and response with the resources which belong to this needs, applying classification techniques to classify the tweets based on the type of needs then use topic modeling to extract the public demand, or extracting needs from data using natural language techniques, information retrieval and rule-based methodology. The process of detecting needs usually focusing to handle one kind of crisis to try understanding the crisis-related keywords and the needs related to the crisis. Therefore, we will focus on detecting needs of affected people in various crises by trying to treat a tweet from affected people as an answer and use question answering techniques which understand the context for each tweet and trying to answer with suitable needs and guidelines without needing know the crisis type.

3. The Proposed Approach Architecture

The people usually think to ask for help or inquire about the instructions in emergency cases during crisis and they may not know the contacts for emergency services. Therefore, the importance of the role of social media like twitter appears because of the speed of which news can be spread as well as the use of hash tags for quicker search. A huge number of tweets is generated from people during a crisis which can be used to detect needs of affected people to provide help. Our proposed approach aims to detect the needs of people during a crisis and answer with the suitable instructions according to the crisis type. The approach passes through several phases showed in Figure 1.

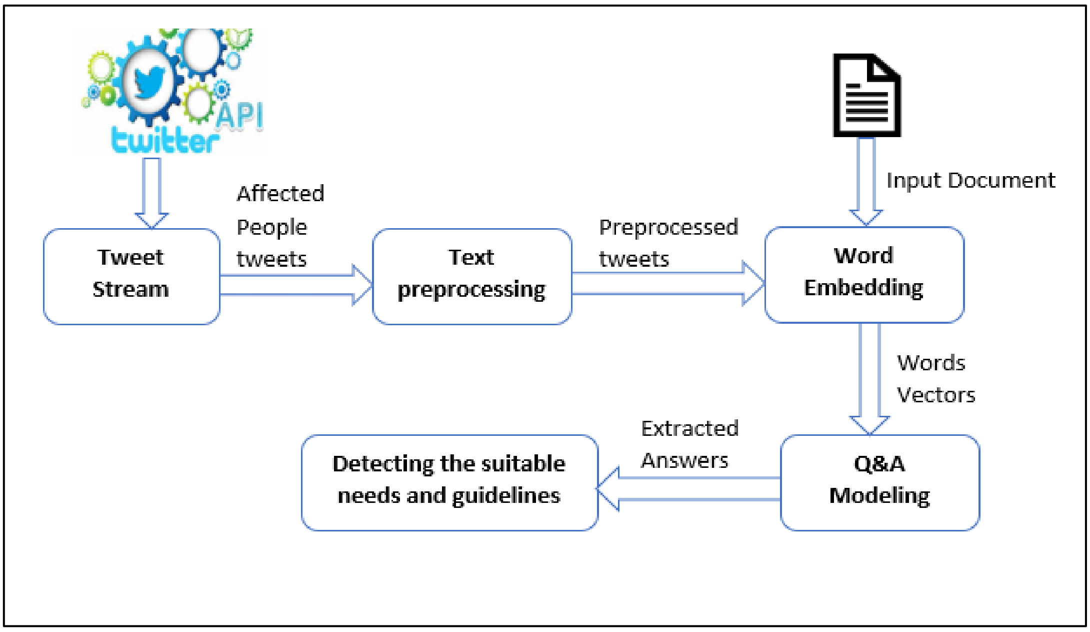

Figure 1. The proposed approach architecture to detect the needs of people

The first step is getting the streaming tweets by using TwitterAPI, and we use filtering keywords in order to get tweets related to a certain crisis.
The next step is using preprocessing techniques to get tokens related to the event. After this step , the next step is "word embedding " to convert text data to the suitable format for Q&A models.
After word embedding, Q&A model is applied to answer with the suitable instructions and needs for each tweet from the people during a crisis.

3.1 Text Preprocessing

Enormous amounts of text data from social media like twitter are being created daily. Tweets are considered as unstructured data which are written in natural language without much consideration of grammar. Therefore, preprocessing is performed on the raw text corpus in anticipation of text mining or NLP task.
The text preprocessing is one of the key components in a typical question answering framework. The process of text preprocessing usually depends on removing stop words, URLs, hashtags and other symbols, extract keywords called tokens, and use normalization and stemming to remove punctuation and convert all words to its standard form without any affixes. But for using Q&A techniques, we must take into account the preservation of the question form, which is the tweet without prejudice to its main meaning. Therefore, the process of preprocessing is limited to the basics as converting all text to lower case , "Noise Removal" involves removing symbols and URLs, and tokenization.
Tokenization is a step which separates longer text into smaller pieces, or tokens, and is considered as "text segmentation" or "lexical analysis". Sometimes segmentation refers to “the breakdown of a large

text into pieces larger than words (e.g. paragraphs or sentences)", while tokenization only refers to the breakdown of text into separate words.

3.2 Word Embedding

Word Embedding is an important step for converting the text data into the suitable format for the Q&A techniques. this technique used to convert words into vector representation which is considered as one of the important steps in the fields of Natural Language processing and neural networks.
Therefore, each word in documents is converted into vector which include numbers as 0 and 1 to represent the word exists or not, and also include values are learned by neural networks algorithms.
The main goal of the low-dimensional representations is the ability to provide a representation that is capable of capturing similarities between features.

3.3 Question Answering techniques

The detection of people's needs during crisis is considered as one of the important goals in the field of crisis management. Therefore, most researches in this field focused on trying to provide approaches to detect the needs to help specially from social networks like Twitter and benefit from Natural Language Processing (NLP).
As mentioned in section 2, most techniques used in detecting needs focus on classification techniques, rule-based methodology, extracting keywords related to the type of needs and semantics techniques. We propose an approach to detect the needs of people in a crisis by using question answering models which depend on neural network algorithms in trying to understand the text and extract the suitable answer related to the text's meaning.

A novel neural network architecture called "transformer" is presented by Google. The transformer is an encoder-decoder architecture model which provide many benefits over the conventional sequential models. It is considered as effective model for long term dependencies among tokens in temporal sequences, also focus on reducing the sequential dependency on previous tokens.[17].

One of the transformers used in NLP effectively for Question and answering techniques is Bidirectional Encoder Representations from Transformer (BERT). BERT trains language models based on the entire set of words in a sentence or query by bidirectional training instead of the ordered sequence of words. Therefore BERT can learn the word context based on surrounding words rather than the word that immediately precedes or follows it.

This model depends on masked language modeling as hiding some words and using its position information to infer. BERT model depends on two steps with the same architecture :(1) pretraining, and (2) finetuning.

The parameters of pretrained model are used to initialize models for different tasks. During finetuning, all parameters are finetuned. In general , There are Two models from BERT according to their different parameters like the number of layers (i.e., Transformer blocks) as L, the hidden size as H, and the number of self-attention heads as A. : The $BERT_{base}$model with standard parameters (L=12, H=768, A=12) and The $BERT_{large}$ model with (L=24, H=1024, A=16). We use the large model which can deal with bigger data than base model.

The input data in BERT is a pair of question and answers, “[CLS]” is a symbol added in front of every input, and “[SEP]” is a separator token to separate between question and answers in each input, as shown in Figure 2 [16].

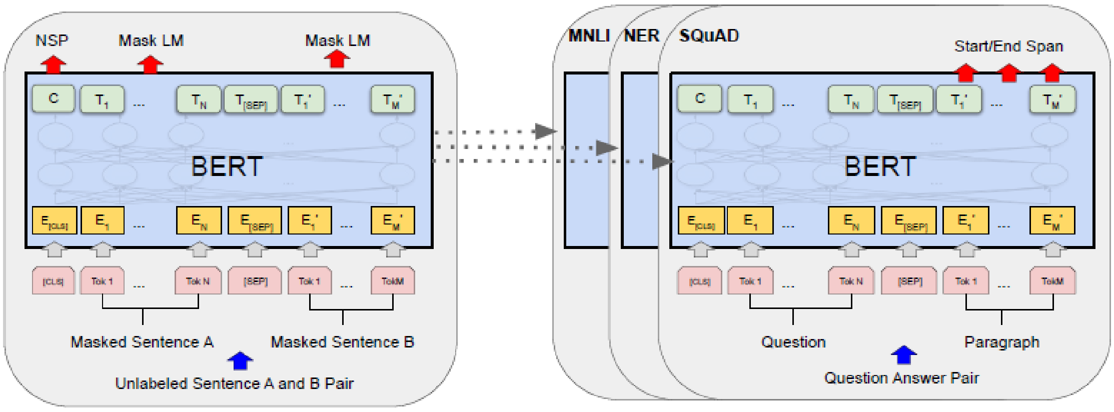

Figure 2. The Architecture of BERT model

BERT is considered as a state-of-art model which follows the standard finetuning paradigm and is trained for normalized benchmarks as SQuAD and GLUE so it may be rare to find some texts longer than the limit for BERT (512 token). Therefore, the datasets can be divided into blocks and insert each block with the question to BERT to extract the answer from each block and choose the block with the max score which describe the relevance for each token [18]. this technique helps us to make BERT dealing with multiple crises at the same time.

4. Experimental results

This section presents the results of the proposed approach.

4.1 Dataset description

We used three datasets both are required as inputs. Tweets of affected people in various crisis are considered as questions, text data about crisis which contain the all guidelines, and answered dataset to test the model.

we used streaming dataset from twitter by using "tweepy" which is a python library from various libraries in different languages used to apply TwitterAPI. The libraries provide search methods to get streaming data returns a collection of relevant Tweets matching a specified query. So, we used some keywords related to crisis as filtering of tweets like earthquake, flooding as shown in Table 1.

Table 1. The Related Keywords

Keywords related to crisis							
Hurricane	Volcano	Earthquake	Fire	Flooding	Typhoon	Explosion	Tornado
help	save	Rescue	damage	storm	whirlpools	Crisis	Disaster

For testing the model, we used open source dataset about COVID-19 which is collected from different official references like World Health Organizations (WHO) as questions and its related answer as shown in Table 2.

Table 2. Examples of Questions and their answers dataset

"Who is at risk of developing severe illness? "	"While we are still learning about how COVID-2019 affects people, older persons and persons with pre-existing medical conditions (such as high blood pressure, heart disease, lung disease, cancer or diabetes) appear to develop serious illness more often than others".
"How long is the incubation period for COVID-19? "	"The incubation period means the time between catching the virus and beginning to have symptoms of the disease. Most estimates of the incubation period for COVID-19 range from 1-14 days, most commonly around five days. These estimates will be updated as more data become available".
"can I catch COVID-19 from my pet?"	"While there has been one instance of a dog being infected in Hong Kong, to date, there is no evidence that a dog, cat or any pet can transmit COVID-19. COVID-19 is mainly spread through droplets produced when an infected person coughs, sneezes, or speaks. To protect yourself, clean your hands frequently and thoroughly. WHO continues to monitor the latest research on this and other COVID-19 topics and will update as new findings are available".
"How long does the virus survive on surfaces?"	"It is not certain how long the virus that causes COVID-19 survives on surfaces, but it seems to behave like other coronaviruses. Studies suggest that coronaviruses (including preliminary information on the COVID-19 virus) may persist on surfaces for a few hours or up to several days. This may vary under different conditions (e.g. type of surface, temperature or humidity of the environment)".

"Is it safe to receive a package from any area where COVID-19 has been reported?"	"Yes. The likelihood of an infected person contaminating commercial goods is low and the risk of catching the virus that causes COVID-19 from a package that has been moved, travelled, and exposed to different conditions and temperature is also low"
"I got my flu shot this year. Can it help me warding off or dealing with COVID-19? "	"The flu vaccine is a very good thing to get every year because it helps reduce the chances of getting the seasonal flu. However, the flu shot does not confer any protection against COVID-19. Despite similar symptoms, the flu shot will not prevent or reduce the severity of COVID-19. "

The second input of the model is a text data about all guidelines of crises which is unstructured format and written in natural language, all these information are collected from different official references according to the type of crisis, as shown in Figure 3.

"Only wear a mask if you are ill with COVID-19 symptoms (especially coughing) or looking after someone who may have COVID-19. Disposable face mask can only be used once. If you are not ill or looking after someone who is ill, then you are wasting a mask. There is a worldwide shortage of masks, so WHO urges people to use masks wisely.
The most effective ways to protect yourself and others against COVID-19 are too frequently clean your hands, cover your cough with the bend of elbow or tissue and maintain a distance of at least 1 meter (3 feet) from people who are coughing or sneezing."

Figure 3. Example of crises guidelines text data

4.2 Evaluation Parameters

This section presents measures for assessing how accurate the Question Answering model is. This evaluation depends on using the testing data, the questions are used as the input with the context data of guidelines, use BERTScore to compare between the real data and the predicted result, use it to compute all evaluation measures.

The Evaluation process of QA model depend on using BERTScore which is a recent metric for evaluating mostly processes like translation, Question answering and image captioning. BertScore require BERT representations of answers in the candidate and reference called "BERT embedding" by feeding the candidate and reference through a BERT model separately [19].

After BERT embedding process, the BERTScore use cosine similarity between candidates and references, extract the maximum similarity score where each token is matched to the most similar token in the other sentence, and compute the evaluation measures recall, precision, f1-score [20].

The Precision (P) and Recall (R) measures are considered as the important measures in testing the NLP techniques. Precision is a measure of "exactness" which is defined as the fraction of relevant instances among all retrieved instances, and Recall is a measure of "completeness" which is defined as the fraction of retrieved instances among all relevant instances. Therefore, BERTScore also provide precision and recall for BERT model, called as Precision BERT and Recall BERT as shown in eq. 1, 2.

$$P_{\text{BERT}} = \frac{\sum \boldsymbol{max\ score\ between\ candidate\ and\ reference}}{\boldsymbol{number\ of\ questions\ in\ dataset}} \quad (1)$$

$$R_{\text{BERT}} = \frac{\sum \boldsymbol{max\ score\ between\ candidate\ and\ reference}}{\boldsymbol{number\ of\ answered\ questions\ from\ model}} \quad (2)$$

The third measure is the F-score which is a way to measure the mean between precision and recall, called "harmonic mean". as shown in eq. 3.

$$\text{F-score}_{\text{BERT}} = \frac{\boldsymbol{2\ xPrecisionxRecall}}{\boldsymbol{Precision+Recall}} \quad (3)$$

4.3 Evaluating Question answering model

In this section, we will discuss the parameters used in building the Question Answering model which depends on answering using either a pre-structured database or a collection of natural language documents. Therefore , we evaluate this model by using the second and third databases mentioned in section 4.1.

The BERT model required 2 major inputs which are the questions and the natural language text data of crises' guidelines. the testing data set contain the questions and its answers. So, we use questions as input for the model with the guidelines and use answers to compare it with the extracted answers from the model which is shown in table 4, to measure the accuracy of model based on the evaluation measures as mentioned in section 4.2. The evaluation results are shown in Table 3.

Table 3. The evaluation measures for BERT model

Evaluation Measures	Precision	Recall	F-Score
	0.81	0.76	0.78

Table 4. Examples of BERT results

Questions	Reference answers	Candidate answers
“Are antibiotics effective in preventing or treating the COVID-19?”	“No. Antibiotics do not work against viruses, they only work on bacterial infections. COVID-19 is caused by a virus, so antibiotics do not work. Antibiotics should not be used as a means of prevention or treatment of COVID-19. They should only be used as directed by a physician to treat a bacterial infection.”	“antibiotics do not work , fight off secondary infections a patient may develop , & they could be vulnerable to complications of covid - 19 , no antiviral drugs available to treat covid - 19 , prevent not yet .& currently there is no vaccine or specific antiviral medicine to prevent or treat covid – 19”
“Should I wear a mask to protect myself?”	“Only wear a mask if you are ill with COVID-19 symptoms (especially coughing) or looking after someone who may have COVID-19. Disposable face mask can only be used once. If you are not ill or looking after someone who is ill then you are wasting a mask. There is a world-wide shortage of masks, so WHO urges people to use masks wisely….”	“people of any age should take preventive health measures like frequent hand washing , physical distancing , and wearing a mask when going out in public , & you should wear a covering over your nose and mouth”

As can be seen from the previous results the BERT model led to the best result which can understand the context of questions and provide the suitable answers.

After testing model, we try the tweet data as input to the model with the guidelines data to extract the needs and instructions for each tweet in different kind of crises. There are examples of answers which extracted from BERT model as shown in table 5.

Table 5. Examples of BERT results from Tweets dataset

Crisis type	tweets	Answers

COVID – 19	"there any foods, supplements, vitamins to prevent or treat COVID-19"	"medicines of therapies, no, then disinfect them . a list of products suitable for use against covid - 19 is available here. this list has been pre - approved by the u.s . environmental protection agency (epa) for use during the covid - 19 outbreak . in addition, wash your hands for 20 seconds with soap and water after bringing in packages , or after trips to the grocery store or other places where you may have come into contact with infected surfaces the flu . & that can reduce the severity of your illness and shorten its duration. there are currently no antiviral drugs available to treat covid - 19, no vaccine or specific antiviral medicine"
COVID – 19	"how to protect from corona"	"physical distancing, wearing a mask , especially when distancing cannot be maintained , keeping rooms well ventilated , avoiding crowds and close contact , regularly cleaning your hands , and coughing into a bent elbow or tissue"
Earthquake	"Can I protect from earthquake, I felt shake before"	"find out what to do before , during , and after an earthquake & step 1 : know the risks and get prepared & move a few steps to a nearby safe place & immediately move inland or to higher ground and remain there until officials declare the area safe . after an earthquake stay calm. help others if you are able. be prepared for aftershocks. listen to the radio or television for information from authorities. follow their instructions. place corded telephone receivers back in their cradles; only make calls if requiring emergency services."
Flooding	"water cover my city, what should I do in flooding?"	"evacuate if told to do so . move to higher ground or a higher floor . stay where you are . how to stay safe when a flood threatens prepare now make a plan for your household , including your pets , so that you and your family know what to do , where to go , and what you will need to protect yourselves from flooding and covid - 19 . build a 'go kit' of the supplies you will need if you have

		to quickly evacuate your home . know types of flood risk in your area . visit fema' s flood map service center for information . sign up for your community ' s warning system . the emergency alert system and national oceanic and atmospheric administration weather radio also provide emergency alerts"

As shown in table 5, BERT can extract the suitable answers for tweets in multiple crises but the tweets are mostly similar to the questions format. The tweets are usually written in unstructured format as natural language and also the limitation of the number of characters in tweets make users to write in abbreviations and not following the standard format of grammar in language. So, it make BERT fail for extracting answers for mostly tweets, because it require the question input in standard grammar format like "I feel unwell #coronavirus" and the BERT answer is "stay".
There are some limitations that arise during the study one of which is the limited availability of test data that represent different crisis situations. The BERT model for Question answering is efficiently dealing with text data in standard question format to understand the question and get the suitable answer but in case of using tweet data we notice that it can deal with the tweets which are similar to question format, better than the tweets in unstructured format. Also as mentioned above in section 3.3, there are limitation with the number of tokens in BERT, it finds difficulty in dealing with big data which contains all guidelines for various crises. so, we separated the text data of crises' guidelines into blocks, each block is inserted to BERT model and apply threading for make model dealing with different crises at same time and reduce time.

5. Conclusion

The accurate identification of the needs of people in crises can be very critical for emergency personnel to provide much needed help. Therefore, the research focus on how can benefit from the large data on social media to provide the help for affected people. The process of needs identification is considered as one of major goals of crisis management process which depends on using Natural language processing techniques and Machine learning. So, we proposed approach that can deal with the data of affected people in various crisis types. Question answering techniques were employed to answer each tweet with the suitable answers for needs and guidelines. These techniques depend on natural language processing, embedding techniques and neural networks. The approach proves that the question answering models can deal with various crises data at same time without need to detect the crisis type or deal with each crisis separately. The approach was tested using Twitter data from various types of emergencies. The results showed that the proposed approach had a precision of 0.81, a recall of 0.76, and an f-score of 0.78 for providing appropriate guidelines. In future work, we will solve the limitation of question answering for dealing with tweet data, which is written in unstructured format, by trying to convert format of tweets to standard question format without any loss of information.

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