MULTIMODAL ANALYSIS OF DISASTER MANAGEMENT

A PROJECT REPORT

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ABSTRACT

Traditional disaster assessment of damage heavily relies on expensive GIS data, especially remote sensing image data. In recent years, social media has become a rich source of disaster information that may be useful in evaluating damage at a lower cost. Such information includes text (e.g. tweets) or images posted by eyewitnesses of disaster and emergency events such as earthquakes, typhoons , floods , tsunami etc. During the sudden onset of a critical situation, affected people resort to social media for a solution and therefore, post useful information (text and images) on Twitter that can be used for situational awareness and other humanitarian disaster response efforts, if processed timely and effectively. But the volume and velocity of tweets posted during crises today tend to be extremely high, making it hard for humanitarian organizations and professional emergency responders to process the information in a timely manner. In this project, we present an automated solution that identifies and matches the request(need) to their corresponding offer(supplies) for textual and imagery twitter data, thereby accelerating the emergency relief efforts. This project stands useful for both the Government and Non-profit Organizations while undertaking Disaster Management and Relief coordination actions.

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CHAPTER 1

INTRODUCTION

At times of natural and man-made disasters, social media platforms such as Twitter and Facebook act as vital information repositories that contain variety of insights such as reports of injured or dead people, infrastructure and utility damage, urgent needs of affected people, and missing or found people among others. Using these insights to solve the crisis is the major motivation behind our proposed system.

1.1 Motivation

Twitter has been extensively used as an active communication platform, especially during critical events such as earthquakes, floods, typhoons, etc. During the onset of such events, a variety of information is posted in real-time by affected people; by people who are in need of help (e.g., food, shelter, medical assistance, etc.) or by people who are willing to donate or offer volunteering services.

Moreover, humanitarian and formal crisis response organizations such as government agencies, public health care NGOs, and the military are tasked with responsibilities such as to save lives, reach people who are in need of help, etc. Situation-sensitive requirements arise during such events and formal disaster response agencies look for actionable, tactical and real-time information to effectively estimate the aftermath of a disaster, and to launch relief efforts accordingly.

At the same time, the volume and velocity of tweets posted during the crisis are extremely high, making it difficult for professional emergency responders to process information in a timely manner. This issue acts as a major motivating factor and is resolved in this project by creating an automated tool for extraction, classification and matching of tweets.

Apart from this, another major motivation for our project is the usage of diverse twitter data such as text, images and videos to gain insight into an event. Although many automated systems based on Artificial Intelligence and Machine Learning have been developed in this field, majority of them focus primarily on analyzing the textual content, ignoring the rich information provided by the visual content. The proposed system addresses this limitation by introducing a real-time social media text and image processing pipeline to assist organizations carry out disaster response and management operations.

Our system acts as a viable tool that matches the requests(need) to the corresponding offers(demand) in the tweets by prioritizing the similar requests based on the severity of the damage observed in the image, where a typical request message involves an entity (person or organization) describing the scarcity of certain resource or service (e.g., clothing, volunteering) and/or plead for immediate help. On the other hand, a typical offer involves an entity describing the availability and/or willingness to supply a resource.

An example scenario for request-offer matching is illustrated in the Figure 1.1 in the form of **use-case** info graphics:

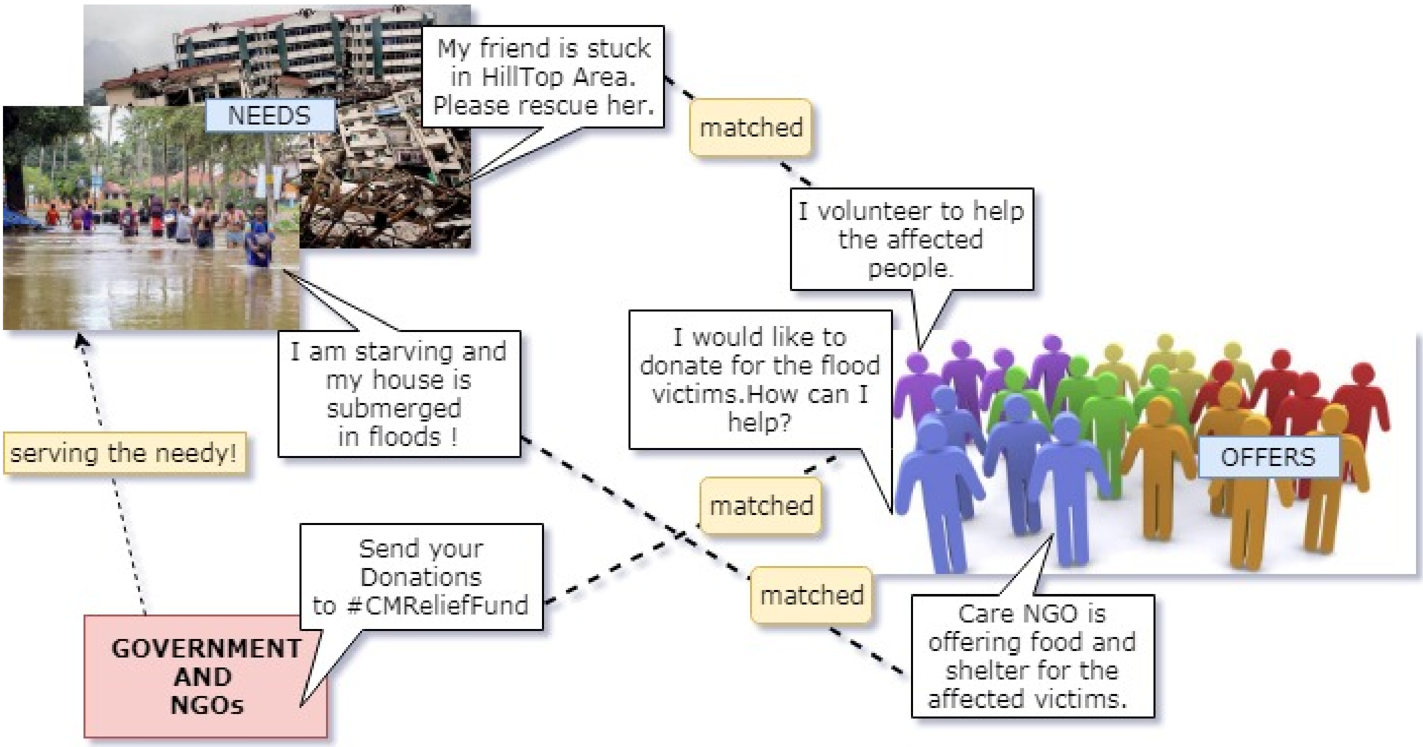

FIGURE 1.1: Use-case Diagram For Request-Offer Matching

The rest of the thesis is organized as follows. The next chapter presents a detailed literature survey of related work followed by Chapter 3 wherein the problem statement of the project is elucidated. Furthermore, the proposed system methodologies, the algorithm and techniques used for the implementation of the individual modules are elaborated in Chapter 4. The results and observations are discussed in Chapter 5. Finally, the conclusion and future work of the project are proposed in Chapter 6.

CHAPTER 2

LITERATURE SURVEY

In this chapter, a detailed description of similar and related work, the methodology used in their work, an analysis of their results and limitations are discussed.

2.1 Related Work

2.1.1 Twitter as a Lifeline: Human-annotated Twitter Corpora for NLP of Crisis-related Messages

In Imran M et al.[7], a human-annotated Twitter corpora collected during 19 different crises that took place between 2013 and 2015 is presented. This human annotations done by volunteers and crowd-sourced workers are of two types. First, the tweets are annotated with a set of categories such as displaced people, financial needs, infrastructure, etc. Second , the tweets are annotated to identify out-of-vocabulary(OOV) terms such as slangs, place names, abbreviations, misspellings, etc. and their corrected normalized forms. This human-annotations is further used to built machine-learning classifiers such as Naive Bayes, Random Forest, and Support Vector Machines (SVM), in a multiclass classification setting, to classify messages that are useful for humanitarian efforts. Also, word2vec word embeddings trained using 52 million crisis-related messages has been furnished.

The system categorizes the data into following categories:

- Request—Disaster victims and humanitarian organizations requesting for help.

- Offer—NGOs and relief measure organizations ready to offer their help.

- Other useful information—Other useful information that helps understand the situation such as

  - Injured or dead people—Reports of casualties and/or injured people due to the crisis.
  - Missing, trapped, or found people—Reports and/or questions about missing or found people.
  - Displaced people and evacuations—People who have relocated due to the crisis, even for a short time (includes evacuations).
  - Infrastructure and utilities damage—Reports of damaged buildings, roads, bridges, or utilities/services interrupted or restored.
  - Caution and advice—Reports of warnings issued or lifted, guidance and tips.
  - Sympathy and emotional support—Prayers, thoughts, and emotional support.

The three different kinds of classifiers are trained using the preprocessed data and the evaluation is done using the 10-folds cross-validation technique. The classification results are calculated in terms of Area Under ROC Curve for selected datasets across all classes using Support Vector Machines (SVM), Naive Bayes (NB), and Random Forest (RF) and are tabulated as shown in Figure 2.1.

Datasets	Classifier	Caution and advice	Displaced people and evaluations	Donation needs or offers	Infrastructure and utilities damage	Injured or dead people	Missing trapped or found people	Sympathy emotional support	Other useful information	Not related or irrelevant
2014 Chile earthquake	Size(%)	15%	2.80%	0.76%	1.70%	5.60%	0.54%	25%	30%	19%
	SVM	0.87	0.89	0.57	0.90	0.97	0.23	0.93	0.86	0.93
	NB	0.86	0.93	0.78	0.88	0.97	0.64	0.93	0.87	0.95
	RF	0.83	0.86	0.67	0.74	0.96	0.46	0.94	0.86	0.92
2015 Nepal earthquake	Size(%)	2.10%	3.10%	28%	4.50%	11%	5.80%	17%	22%	6.50%
	SVM	0.47	0.80	0.89	0.85	0.95	0.86	0.88	0.76	0.75
	NB	0.68	0.82	0.91	0.90	0.95	0.89	0.91	0.79	0.84
	RF	0.56	0.73	0.89	0.74	0.94	0.87	0.89	0.76	0.75
2013 Pakistan earthquake	Size(%)	6.30%	0.82%	15%	2%	17%	0.49%	5.60%	35%	18%
	SVM	0.77	0.80	0.92	0.76	0.95	0.63	0.82	0.84	0.84
	NB	0.82	0.87	0.94	0.91	0.93	0.74	0.83	0.84	0.84
	RF	0.68	0.70	0.92	0.77	0.95	0.69	0.78	0.88	0.83
2015 Cyclone Pam	Size(%)	7%	3.10%	17%	11%	7.20%	1.30%	5%	25%	24%
	SVM	0.76	0.80	0.92	0.85	0.95	0.39	0.66	0.77	0.90
	NB	0.79	0.82	0.92	0.86	0.97	0.56	0.79	0.80	0.94
	RF	0.68	0.80	0.90	0.80	0.95	0.47	0.71	0.79	0.92
2014 Typhoon Hagupit	Size(%)	20%	6.60%	5.50%	5.10%	3%	0.58%	13%	33%	13%
	SVM	0.74	0.95	0.88	0.76	0.94	0.44	0.92	0.74	0.81
	NB	0.75	0.96	0.89	0.82	0.96	0.57	0.92	0.78	0.81
	RF	0.71	0.97	0.84	0.73	0.94	0.58	0.91	0.75	0.80
2014 India floods	Size(%)	3.60%	1.40%	2.60%	4.30%	47%	0.87%	1.30%	14%	25%
	SVM	0.82	0.80	0.92	0.92	0.97	0.66	0.63	0.87	0.97
	NB	0.89	0.92	0.93	0.90	0.93	0.79	0.83	0.89	0.98
	RF	0.83	0.79	0.86	0.87	0.97	0.66	0.65	0.91	0.96
2014 Pakistan floods	Size(%)	3.90%	6.20%	25%	5.40%	13%	6.40%	6%	32%	2.30%
	SVM	0.71	0.84	0.82	0.77	0.94	0.85	0.88	0.74	0.47
	NB	0.83	0.80	0.85	0.79	0.94	0.85	0.89	0.77	0.65
	RF	0.72	0.80	0.87	0.78	0.95	0.84	0.86	0.79	0.59
2014 California earthquake	Size(%)	6.30%	0.48%	4.30%	18%	10%	0.51%	4.10%	47%	9.40%
	SVM	0.84	0.54	0.93	0.88	0.97	0.62	0.84	0.77	0.72
	NB	0.88	0.57	0.94	0.86	0.97	0.79	0.90	0.78	0.77
	RF	0.81	0.49	0.87	0.89	0.98	0.57	0.88	0.81	0.77

FIGURE 2.1: Classification results in terms of Area Under ROC Curve using Support Vector Machines (SVM), Naive Bayes (NB), and Random Forest (RF).
Source: [7]

2.1.2 A Twitter Tale of Three Hurricanes: Harvey, Irma, and Maria

In Alam F et al.[1], an extensive multidimensional analysis of textual and multimedia content is conducted from millions of tweets, shared on Twitter, collected during the three disasters, namely Hurricanes Harvey, Irma, and Maria. The objective of this paper includes the following tasks. First, perform sentiment analysis to determine how people's thoughts and feelings change over time as disaster events progress. Second, employ topic modeling techniques to gain insight into the different topics discussed during each day, in order to help concerned authorities to quickly sift through big crisis data. Furthermore, classify both textual and imagery content into several humanitarian categories as mentioned in [7]. The data collected from CrisisNLP repository[7] is made use for the analysis.

To perform the sentiment analysis, the Stanford sentiment analysis classifier that classifies the text into 5 categorical labels such as Very Negative, Negative, Neutral, Positive and Very Positive is made use. The accuracy of the classifier for fine-grained sentiment labels is 80.7%. The classification of humanitarian categories is performed using a decision tree based learning scheme known as Random Forest. The performance obtained using the test set in terms of the F-measure is F1 = 0.64 and accuracy of 0.66.

The topic modelling is evaluated using LDA (Latent Drichlet Allocation) method to obtain the top 30 frequently used terms. Standford NER tagger is used for the identification of most mentioned named entities that helps in discovering important stories related to actual local emergency needs. The reported F-measure of this NER system is 86.72% to 92.28% for different datasets.

The images are classified as severe, mild and none and are trained based on the human annotated ground truth values using their relevancy filtering model. The overall accuracy of the resulting damage assessment models varies from 76% to 90%.

The major limitation of this work is that it is semi-automated and requires human in the loop for machine training. Further, it does not address the scalability issues that arise owing to the volume of data being processed.

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2.1.3 Damage Assessment from Social Media Imagery Data During Disasters

In Nguyen D T et al.[8], determination of the level of destruction caused by the disasters has been performed. In this study, labeled data from past disaster events as well as data collected from the Web have been leveraged. These data resources are further annotated using the Crowdflower (Crowdsourcing platform) based on fixed guidelines. For damage assessment, three levels namely : severe damage, mild damage, and little-to-no damage are taken into consideration. This work employs both traditional computer vision techniques such as Bag-of-Visual-Words (BoVW) model as well as state-of-the-art deep learning techniques such as Convolutional Neural Networks (CNN) to assess the level of destruction in disaster images.

The event specific experiments using the three learning techniques (i.e. BoVW, VGG16-fc7, and VGG16-fine-tuned) are evaluated in terms of precision, recall, F1 score and overall accuracy as shown in Figure 2.2. The experimental analysis of this work shows that domain-specific fine-tuning of deep CNNs outperforms the traditional BoVW models by a considerable margin. However, there are two main challenges, i.e. low prevalence of the training data and non-trivial human-labeling tasks in this work.

	Nepal Earthquake				Ecuador Earthquake			
	Acc.	Precision	Recall	F1	Acc.	Precision	Recall	F1
BoVW	0.78	0.77	0.78	0.77	0.82	0.81	0.82	0.81
VGG16-fc7	0.76	0.76	0.76	0.76	0.82	0.82	0.82	0.82
VGG16-fine-tuned	**0.84**	**0.82**	**0.84**	**0.82**	**0.87**	**0.86**	**0.87**	**0.86**
	Hurricane Matthew				Typhoon Ruby			
	Acc.	Precision	Recall	F1	Acc.	Precision	Recall	F1
BoVW	0.64	0.64	0.66	0.64	0.73	0.74	0.73	0.72
VGG16-fc7	0.63	0.63	0.64	0.63	0.79	0.80	0.80	0.80
VGG16-fine-tuned	**0.74**	**0.73**	**0.74**	**0.74**	**0.81**	**0.80**	**0.81**	**0.80**
	Google Image							
	Acc.	Precision	Recall	F1				
BoVW	0.57	0.53	0.56	0.54				
VGG16-fc7	0.60	0.63	0.64	0.63				
VGG16-fine-tuned	**0.67**	**0.67**	**0.67**	**0.67**				

FIGURE 2.2: Event-specific results in terms of precision, recall, f1 score, and overall accuracy using three different learning schemes.
Source:[8]

2.1.4 Aid is Out There: Looking for Help from Tweets during a Large Scale Disaster

In Varga I et al.[12], a method for discovering matches between problem reports and aid messages is proposed. This system contributes to problem-solving during large scale disaster situations by facilitating communication between victims and humanitarian organizations. A machine learning based system is developed to recognize problem reports and aid messages followed by problem-aid tweet matching.

First, location names in tweets are identified by matching tweets against their location dictionary. Then, each tweet is paired with the dependency relation in the tweet, which is referred to as the nuclei and given to the problem report and aid

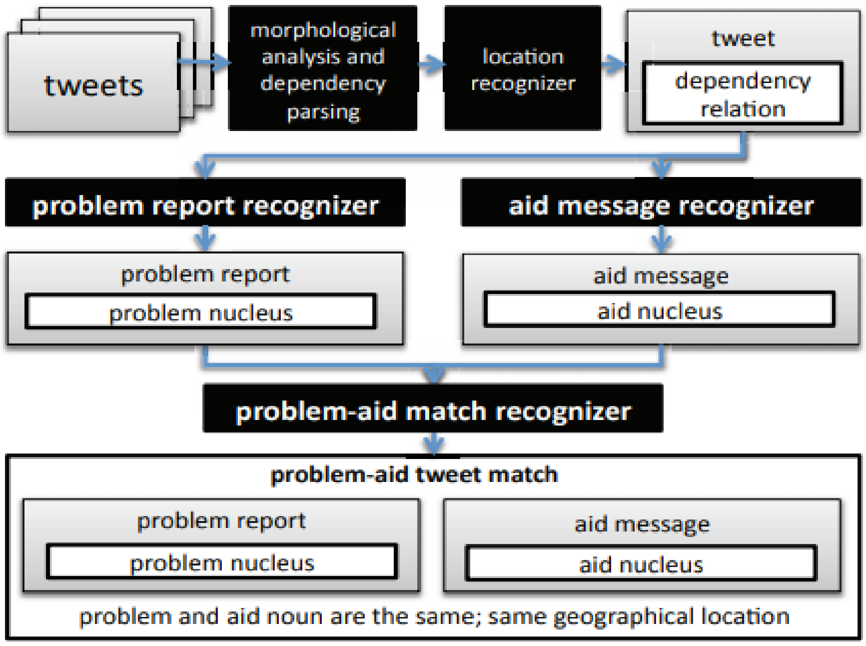

FIGURE 2.3: Problem-aid matching system overview.
Source:[12]

message recognizer. A tweet-nucleus-candidate pair judged as problem report is combined with another tweet-nucleus-candidate pair recognized as an aid message if the two nuclei share the same noun and the tweets share the same location name. In this work, structural characteristics of tweets are not employed as restrictions (e.g. a problem report and its aid message need to be in the same tweet chain).

2.1.5 CrisisMMD: Multimodal Twitter Datasets from Natural Disasters

In Alam F et al.[2], human-labeled multimodal datasets collected from Twitter during seven recent natural disasters including earthquakes, hurricanes, wildfires, and floods are presented. The tweets that do not contain at least one image URL are filtered out and the rest of the data are annotated by paid workers, from a well-known crowdsourcing platform, based on three humanitarian tasks. The first task aims at categorizing the data into two high-level classes namely Informative and Not informative. The second task, on the other hand, aims at identifing critical and potentially actionable information such as reports of injured or dead people, infrastructure damage, etc. from the tweets. For this purpose, seven humanitarian categories are used. The final task aims at assessing the severity of damage shown in the images. The severity of damage is based on the extent of physical destruction to a building structure. Firstly, the task one is executed by human annotators, and only the informative tweets are passed to task two. In second task, the images are annotated manually and only those included in the 'infrastructure and utility damage' category are given to task three. In task three, the images are classified as severe, mild and no damage categories. To conclude, this manually labelled dataset is useful to address a number of crisis response and management tasks for different humanitarian organizations and is available as CrisisMMD which is published at the CrisisNLP site.

2.1.6 Rapid Classification of Crisis-related Data on Social Networks using Convolutional Neural Networks

In Nyugen D T et al.[9], neural network based classification methods for binary and multi-class tweet classification task is presented. Twitter data from multiple sources: (1) CrisisNLP, (2) CrisisLex, and (3) AIDR are used. The data are preprocessed and tokenized using the CMU TweetNLP tool. The unigram, bigram and trigram features are then extracted from the tweets as features. The features

SYS	RF	LR	SVM	CNN_I	CNN_{II}
Nepal Earthquake					
B_{event}	82.70	85.47	85.34	**86.89**	85.71
B_{out}	74.63	78.58	78.93	81.14	78.72
$B_{event+out}$	81.92	82.68	83.62	84.82	84.91
California Earthquake					
B_{event}	75.64	79.57	78.95	**81.21**	78.82
B_{out}	56.12	50.37	50.83	62.08	68.82
$B_{event+out}$	77.34	75.50	74.67	78.32	79.75
Typhoon Hagupit					
B_{event}	82.05	82.36	78.08	87.83	**90.17**
B_{out}	73.89	71.14	71.86	82.35	84.48
$B_{event+out}$	78.37	75.90	77.64	85.84	87.71
Cyclone PAM					
B_{event}	90.26	90.64	90.82	**94.17**	93.11
B_{out}	80.24	79.22	80.83	85.62	87.48
$B_{event+out}$	89.38	90.61	90.74	92.64	91.20

FIGURE 2.4: Performance Comparison based on AUC.
Source:[9]

are converted to TF-IDF vectors by considering each tweet as a document. These features are used by the non-neural models. Some of non-neural existing models including: (i) Support Vector Machine (SVM), (ii) Logistic Regression (LR), and (iii) Random Forest (RF) are experimented with for comparision.

A CNN model is trained by optimizing the cross entropy and maximum number of epochs as 25. Various dropout rates and minibatch sizes are experimented with and rectified linear units (ReLU) is used for the activation function. The CNN model is initialized using two types of pretrained word embeddings. (i) Crisis Embeddings (CNN1) : trained on all crisis tweets data (ii) Google Embeddings (CNN2) trained on the Google News dataset.

The results of classification by several non-neural classifiers is compared with the CNN based classifier using the AUC (Area under the ROC) score as shown in Figure 2.4. Clearly, CNN outperforms the traditional non-neural methods. The drawback in this work is that CNN does not consider the semantic relatedness of a tweet under several classes which brings inconsistency in labeling.

CHAPTER 3

PROBLEM STATEMENT

The proposed system takes real-time twitter data and maps the request tweets to their corresponding offer tweets by taking both the text and image into consideration.

3.1 Input

Real-time social media data containing either only text or both text and one or more images.

FIGURE 3.1: Tweets containing textual contents only.
Source: https://twitter.com/

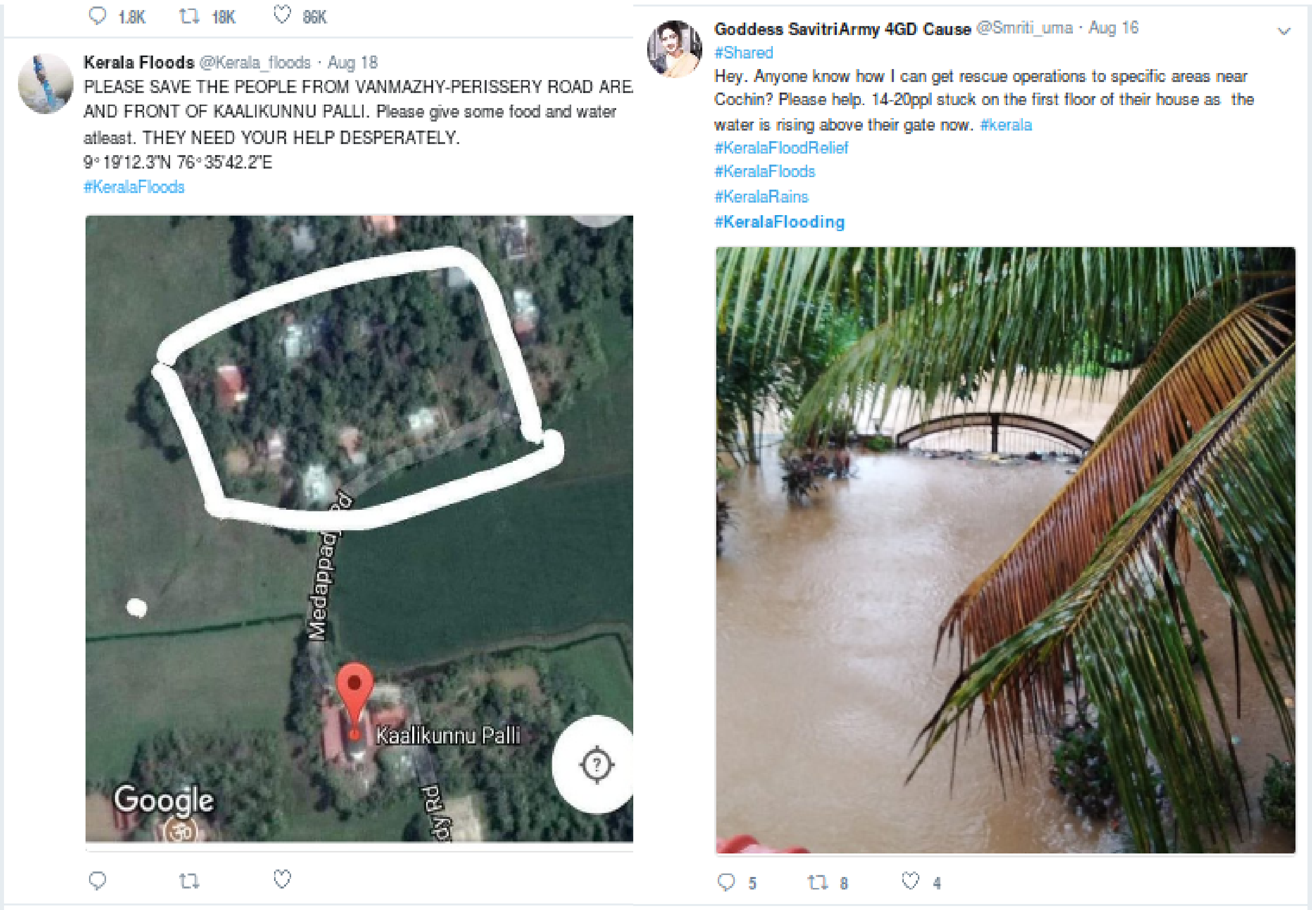

FIGURE 3.2: Tweets containing both text and image.
Source:https://twitter.com/

3.2 Output

Matched (request,offer) pairs based on requirements and severity of the damage that helps in carrying out relief operations

3.3 Use Case

The proposed system can be employed to assist the Government and humanitarian organizations to launch relief operations immediately in disaster-hit regions.

CHAPTER 4

PROPOSED SYSTEM METHODOLOGY

The proposed system aims at multimodal analysis for disaster management which involves real time analysis of both text and image from social media in order to help the government as well as humanitarian organizations to perform relief operations immediately.

The pipeline of the system consists of 4 phases: **Collection, Preprocessing, Classification, Prioritization and Matching.**

The proposed system architecture is illustrated in Fig 4.1.

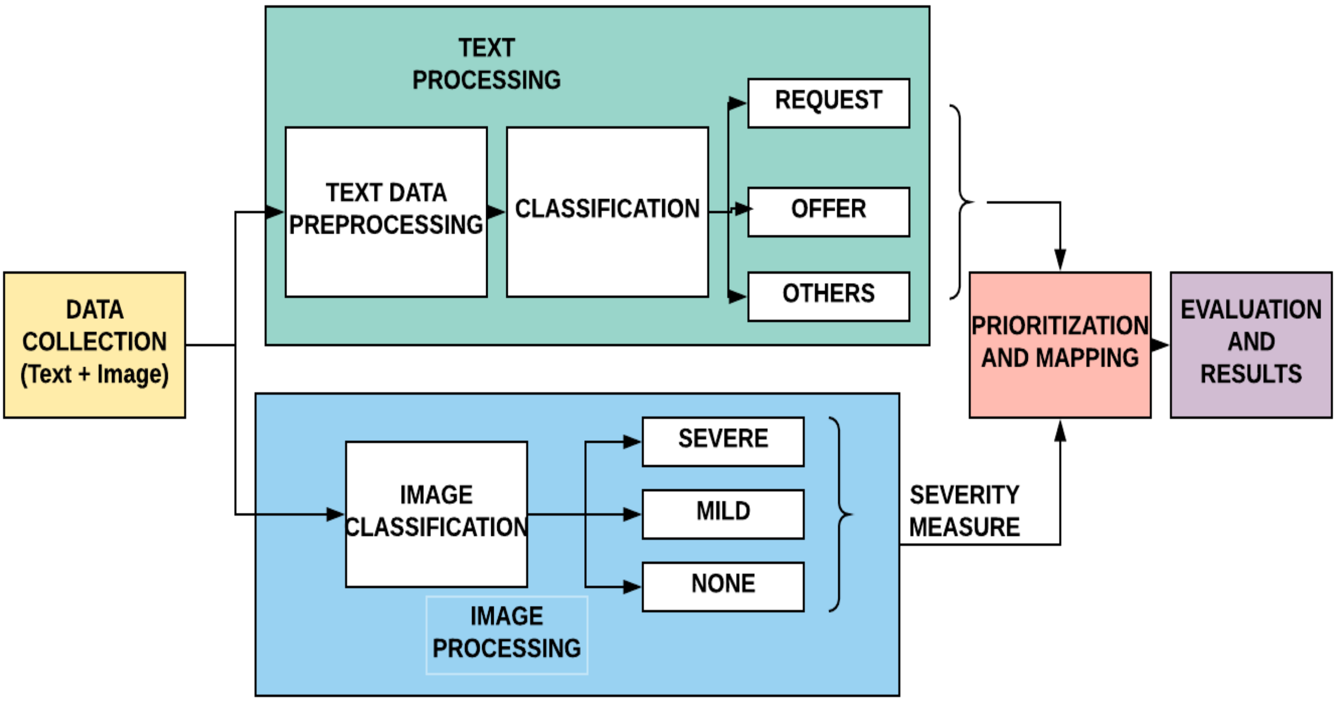

FIGURE 4.1: Proposed System Architecture

```
Result: matched_tweets
while true do
    hashtag = trending_hashtags(APIcredentials, location);
    if check(hashtag) /* Disaster based hashtag */ then
        tweets = extract_tweets(APIcredentials, hashtag);
        tweets = preprocess(tweets);
        for t ←tweets do
            if contains(t,onlytext) then
                [request,offer] ← classify_text(t);
            else
                /* contains both text and image */
                  [request,offer] ← classify_text(t);
                priority* ← classify_image(t);
            end
        end
        matching ← match(request,offer)
    else
        continue;
    end
end
*Priority is computed only for the request tweets.
```

Algorithm 1: Proposed System Algorithm

4.1 Data Collection

The Collection phase includes real-time extraction and analysis of both textual and imagery tweets that are relevant to a particular ongoing disastrous event. The live tweets pertaining to disasters are fetched based on their hashtag. The Tweepy API, an open source python library, is imported for the retrieval of the twitter data. The working of the live tweets collection module is shown in Fig 4.2.

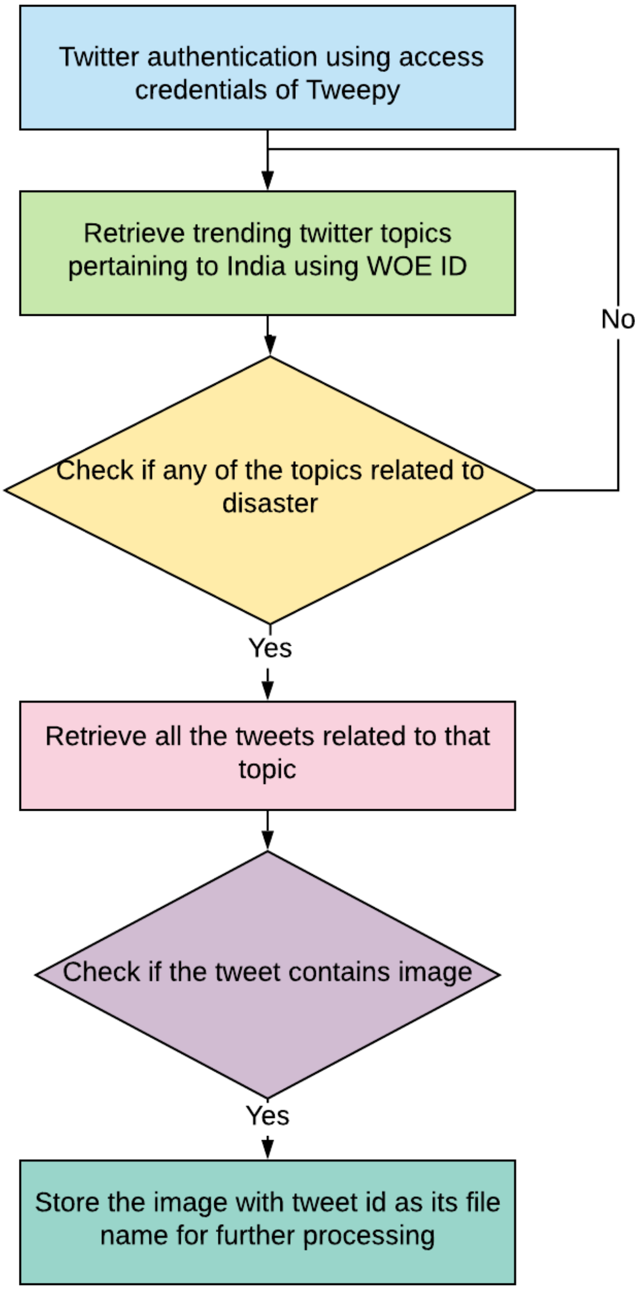

FIGURE 4.2: Flowchart depicting Live Tweets Collection

The stepwise implementation of the algorithm is stated as follows:

1. The Twitter access is authenticated by providing the consumer_key, consumer_secret, access_token and access_token_secret of the registered twitter user.

2. The trending hashtags of India is collected by providing India's WOE_ID i.e. Where On Earth Identifier.

3. The list of trending hashtags are analysed for the presence of a disaster using keywords like avalanche, volcano, earthquake, disaster, tsunami, tornado, drought, storm, flood and tremor.

4. If a disaster is found, the corresponding tweets (both text and image) are extracted by specifying the hashtag. The images are detected using the media URL and stored with its respective tweet id as its filename.

Algorithm 2: Live Tweets Extraction

Therefore, the incoming tweets are split into textual and imagery content and stored separately. The stored textual tweets are given as input to the next module.

4.2 Data Preprocessing

The stored tweets from the previous module are then preprocessed. Several preprocessing tasks are performed on the input data using the tweet preprocessor API.

The tweet text are converted to uniform lower case characters. The URLs, SMILEYs/EMOJIs and USER MENTIONS (@) are cleaned off from the text.

Repetition of tweets are avoided by removing retweets (RT). The hashtagged words are retained by the removing the '#' prefix from #word.
The HTMLParser module is employed to parse the text file formatted in HTML and XHTML, which includes changing of escape sequences like & to &. Further, the tweet texts are normalized by changing the short forms such as 're, 'nt, 've to are, not, have, etc.
Finally, the non-ASCII and special characters are removing from the text. This preprocessed text is provided as input to the text classification module which is explained in the forthcoming section.

4.3 Classification

The preprocessed tweets from the previous module and the images stored at the 'Data Collection module' are given as input to this Classification module. Here, the text and image classification are done separately. The text classification is performed using LSTM and the image classification is carried out using Convolutional Neural Network.

4.3.1 Text Classification Using LSTM

The Text Classification phase segregates the extracted data into three categories namely:

- Request—Disaster victims and humanitarian organizations requesting for help.

- Offer—NGOs and relief measure organizations ready to offer their help.
- None — The tweet is neither a request nor an offer.

In order to handle sequential data, Recurrent Neural Network (RNN) is implemented for this purpose. Due to the problem of vanishing gradients, Long Short Term Memory(LSTM) model is constructed.

We have implemented and tested out two variations of the text classification model using LSTM : Variation 1 and 2. These two models were compared and the more efficient one has been employed in our final proposed system.

In the following sections, the dataset used for training this text classification model is elaborated and both the LSTM models (Variation 1 and 2) are explained and compared.

4.3.1.1 Dataset

The dataset for training was obtained from a resource published by Quatar Computing Research Institute(QCRI) group called CRISISNLP under the title Human-annotated Twitter Corpora for NLP of Crisis-related Messages[7].

This dataset[7] contains human annotated data for 10 different disasters that took place between 2013 and 2015 having more than 2000 labelled tweets each created by crowdsource workers. The data has been manually classified into 9 categories namely :

1. Injured or dead people
2. Missing, trapped, or found people
3. Displaced people and evacuations
4. Infrastructure and utilities damage

	A	B	C	D
1	timestamp	label	tweetid	tweettext
2	02-07-2016 17:44	request	'508332173532073985'	joydas please use kashmir flood hashtag only if u need help or offering help so that agencies can track keep it free from ur politica
3	02-07-2016 10:58	offer	508332187448401920'	klasrarauf pungovt claims cmss took 9 helicopter flights2south punjab in1day to monitor floods oh i got itfloods got frightenedampnow e
4	02-07-2016 11:15	offer	'508332198714294272'	timesofindia jampk floods helpline numbers httptcoog4gwlqmgs do kashmirfloods httptcoeoq4ojrfe5
5	02-07-2016 11:35	offer	'508332247867355136'	united nations authority flood rescue operations in kashmir india httptcocqt4jpvyjv
6	02-07-2016 11:11	offer	'508332271381008384'	doctoratlarge meanwhile aamir khan is so pained by kashmir floods that he will dedicate an entire smj episode on it and earn another
7	02-07-2016 12:27	offer	'508332273280622592'	arvindkejriwal all aap mlas to donate rs 20 lakh each for kashmir flood relief from their mla funds
8	02-07-2016 13:01	offer	'508332287524499456'	hey ive just donated rs 10 for kashmir flood relief through hikeapp hike4kashmir
9	02-07-2016 11:50	offer	'508332291190689792'	officialmqm mqm charity wing kkf lahore have setup flood relief camps in all over punjab httptcocahi83juyn
10	02-07-2016 11:28	offer	'508332411315167232'	tterindia dear rupasubramanya pm modi gave 1000 cr to kashmir flood was that public money or jasodaben fixed depost httptco
11	02-07-2016 19:11	offer	'508332439756754944'	officialmqm kkf distributing relief goods among victims of flood in different districts of punjab httptcotbyiew8agq mqm http
12	02-07-2016 12:07	request	'508332473583808512'	donate for kashmir floods httptcoed0dcwc9q8
13	02-07-2016 16:59	RO	'508332502600015872'	pakistan floods cabinet decides against appeal for foreign aid
14	02-07-2016 19:09	offer	'508332506349711360'	ddnewsbreaking people in flood affected areas of poonch jampk provided healthcare and relief material kashmirfloods httptcon6lkt
15	02-07-2016 13:34	offer	'508332520103243776'	kashmir floods the tireless service of a battalion and its boats httptcorrzcxm3fmf
16	02-07-2016 11:19	offer	'508332534464118784'	shahidloverz sashahoture shahidkapoor is helping the kashmirflood victims but doesnt want it to be a promotional event we
17	02-07-2016 14:07	RO	'508332572988813312'	majoramkhan proudly serving pakistan satisfaction while helping your countrymen at the time of need help the flood victims http
18	02-07-2016 15:34	request	'508332632908652544'	charity for kashmir and indian flood disaster httptcoinwdwftlj7
19	02-07-2016 15:39	offer	'508332642014478336'	kashmir floods medical camps in srinagar to check waterborne diseases the national disaster response force httptcoz6395likw5
20	02-07-2016 11:19	offer	'508332660662337536'	kyayaarkuchbi hindus r welcome in my home at jammu rescued from kashmir floodsmuslims can fuck themselvesdm me if u need shelter

FIGURE 4.3: Sample text dataset

5. Donation needs or offers or volunteering services
6. Caution and advice
7. Sympathy and emotional support
8. Other useful information
9. Not related or irrelevant

Out of these nine categories, 'Donation needs or offers or volunteering services' alone were scrapped out for our purpose.

Around 6000 human annotated request and offer tweets were utilized to build and test the model. 80% of the dataset was used for training (precisely 4425 tweets) and the remaining 20% for testing.

4.3.1.2 Text Classification Model Architecture using LSTM (Variation 1)

An initial LSTM model was built as shown in Fig 4.4 with one embedding Layer followed by a unidirectional LSTM layer and then a fully connected dense layer.

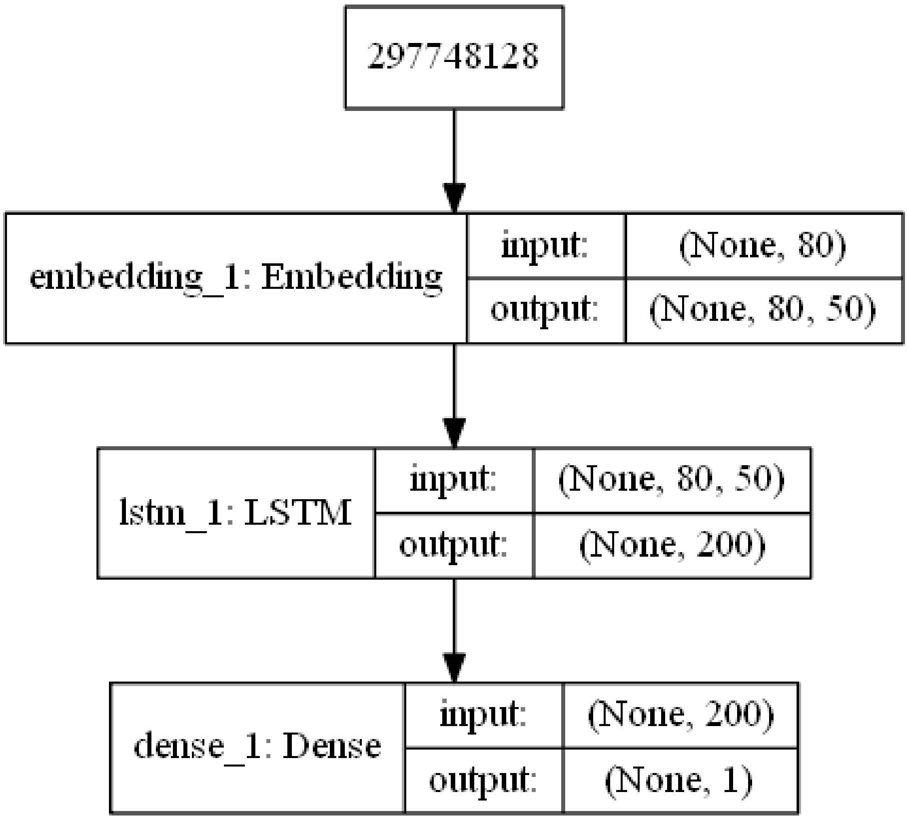

FIGURE 4.4: Text Classification Model Architecture using LSTM (Variation 1)

4.3.1.3 Text Classification Model Architecture using LSTM (Variation 2)

The performance of the initial model was improved by making certain changes to the architecture. These changes are tabulated in Table 4.1.

This improved model contains an initial pretrained Glove embedding layer, two stacked bidirectional LSTM layers followed by a dense fully connected layer.

The model plot of LSTM variation II is illustrated as shown in Fig.4.5.

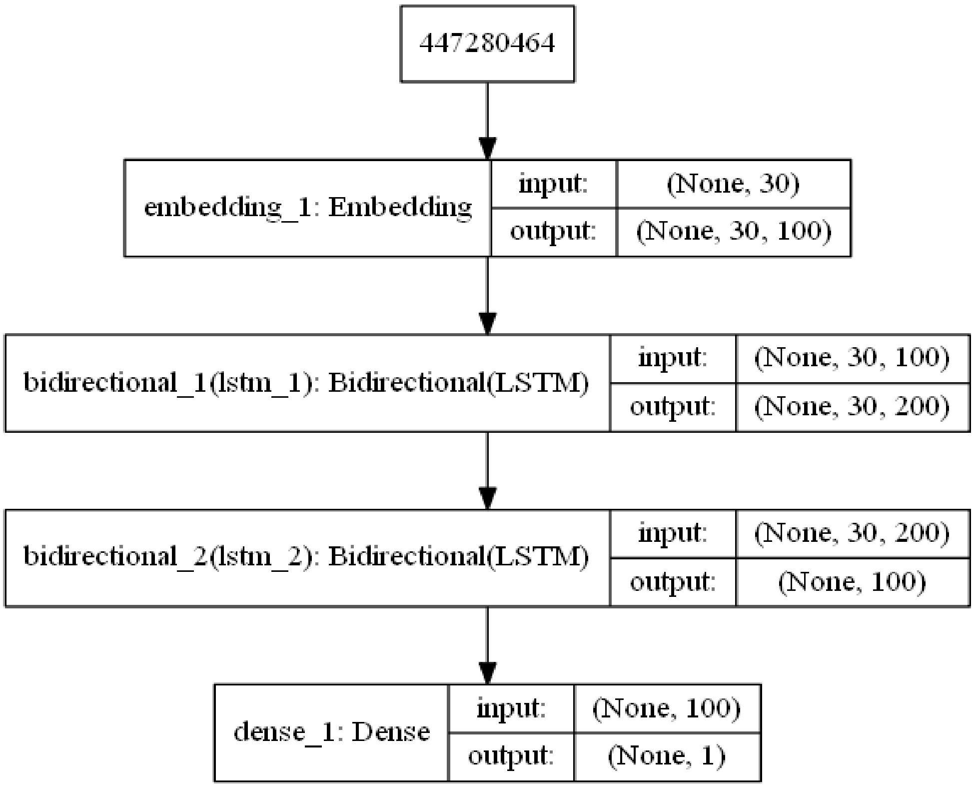

FIGURE 4.5: Text Classification Model Architecture using LSTM (Variation 2)

TABLE 4.1: Improvement in the LSTM model

	VARIATION 1	**VARIATION 2**
1.Preprocessing	Basic text preprocessing.	Improved preprocessing using tweet preprocessor package.
2.Vocabulary Size	Fixed as a constant value-20000.	Set as the number of unique words in the vocabulary
3.Embedding	A seperate layer for creating the word embeddings.	Word vectors are created using “pretrained Glove embeddings”
4.Padding	A constant padding length as 50 was set.	Fixed as the maximum number of words appearing in a tweet in the dataset (=30).
5.LSTM	Single Unidirectional LSTM Layer - Learning from past to future	Two stacked Bidirectional LSTM Layers

4.3.2 Image Classification using CNN

The image classification phase classifies the input image associated with request tweets into three categories namely : 1. Mild, 2. Severe, and 3. None. This provides insight into the gravity of the damage inflicted by the disaster.
We have implemented and tested out two variations of the image classification model : an initial model using CNN and modified VGG-16 model. These two models were compared and the more efficient one has been employed in our final proposed system.
In the following sections, the dataset used for training this image classification model is elaborated and both the CNN models are explained and compared.

4.3.2.1 Dataset

The dataset for training the image classification model was obtained from a resource cited in Damage Assessment from Social Media Imagery data During Disasters.

This dataset[1] has been developed for the purpose of assessing the damage during disasters using social media images collected during 4 natural disasters like Typhoon Ruby(2014), Nepal Earthquake(2015), Eucador Earthquake(2016), Hurricane Mathew(2016) and google images. The infrastructure and utility damage images(relevant) are classified as severe, mild and little or no damage categories. It has a total of 25820 such images. The image dataset comprises of 19703 images, out of which 15258 images were used for training and the remaining 3815 images were used for testing i.e. 80% training data and 20% testing data.

4.3.2.2 Initial model

The input images were resized to a common, fixed size (224x224). An initial basic CNN model was designed with two layers of convolution. The architectural summary of this model is shown in Figure 4.7.

FIGURE 4.6: Image Dataset Sample

In an attempt to improve the performance of the model, an alternate pre-trained VGG-16 model was fine tuned using transfer learning technique.

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 222, 222, 32)	896
activation_1 (Activation)	(None, 222, 222, 32)	0
conv2d_2 (Conv2D)	(None, 220, 220, 32)	9248
activation_2 (Activation)	(None, 220, 220, 32)	0
max_pooling2d_1 (MaxPooling2	(None, 110, 110, 32)	0
dropout_1 (Dropout)	(None, 110, 110, 32)	0
flatten_1 (Flatten)	(None, 387200)	0
dense_1 (Dense)	(None, 128)	49561728
activation_3 (Activation)	(None, 128)	0
dropout_2 (Dropout)	(None, 128)	0
dense_2 (Dense)	(None, 3)	387
activation_4 (Activation)	(None, 3)	0

Total params: 49,572,259
Trainable params: 49,572,259
Non-trainable params: 0

FIGURE 4.7: Image Classification Model Architecture using CNN

4.3.2.3 Transfer learning using VGG-16

CNNs are rarely trained from scratch for new datasets because state-of-the-art CNNs (i) are getting deeper everyday, and (ii) require larger datasets to train on. However, collecting large datasets for the particular problem at hand is usually hard in practice (as in the current study). Therefore, it is common to devise new techniques based on pre-trained networks.

A popular approach is to use the existing weights of a pre-trained CNN as an initialization for the new dataset, which is often referred to as fine-tuning. In the transfer-learning approach, the last layer of the network is adapted to the task at hand (i.e., number of categories in the softmax layer and sometimes even the loss function) and the pre-trained network is fine-tuned according to the training images from the new dataset. This approach allows us to transfer the features and the parameters of the network from the broad domain (i.e., large scale image classification) to the specific one (i.e., disaster image analysis).

We adapted the VGG-16 network, pre-trained on the ImageNet dataset, to

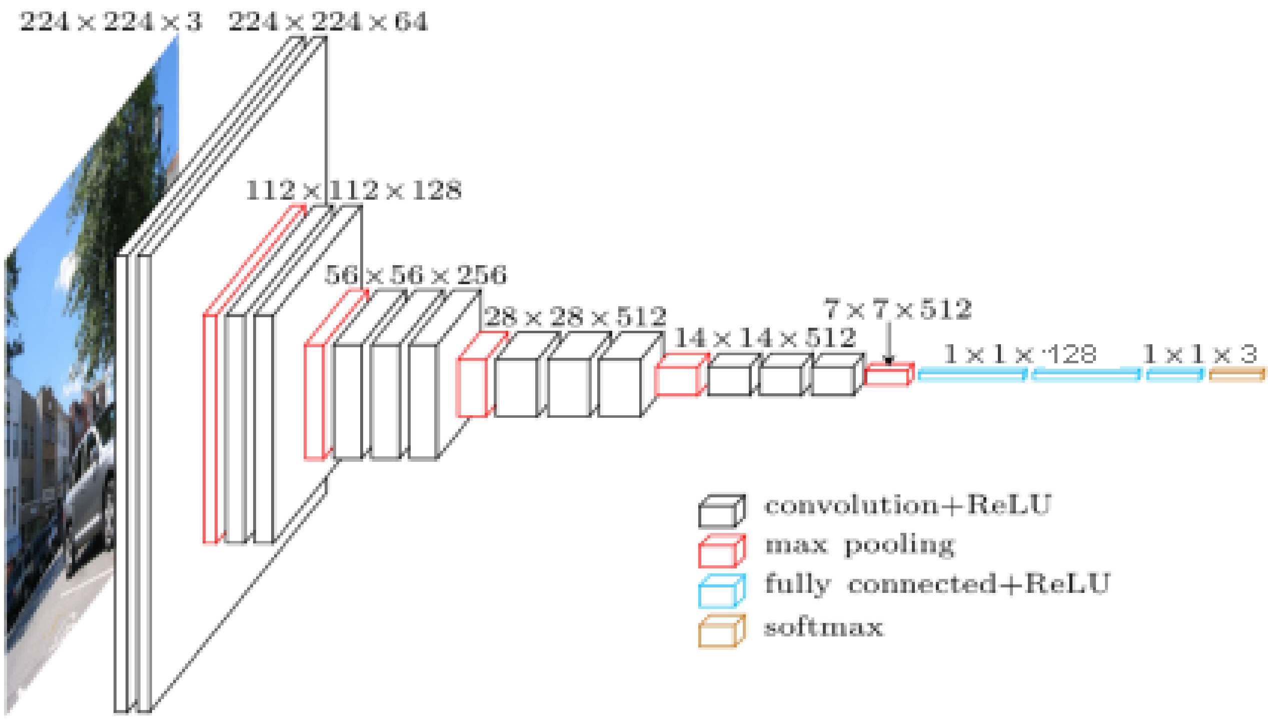

FIGURE 4.8: Architecture Diagram of Modified VGG-16
Source:https://www.cs.toronto.edu/ frossard/post/vgg16/

classify the images in our disaster image dataset into one of the three damage categories namely severe, mild, and none. The VGG-16 network trained on the ImageNet dataset uses over 1.2M images and 1000 categories. The VGG-16 network consists of 16 layers and around 140 million weight parameters.

The weights until the block5_pool layer were retained and these layers were flagged False for training. A Flatten layer followed by two dense fully connected layers were added and finally a dense Softmax layer with three outputs was included. Features were computed by forward propagating a 224 x 224 RGB image through thirteen convolutional, five max pooling layer, two fully connected dense layers and finally the softmax layer.

The image classification model architecture using modified VGG-16 is shown in Fig.4.8. The architectural summary of the model is given in Fig. 4.9.

4.3.3 Merging Text and Image Classification Results

The independent outputs of the text and image classification modules are combined together by merging them based on the common tweet_id. The resulting intermediate output containing tweet_id, tweet_text, text_label, image_severity as its attributes are given as input to the next matching module.

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	(None, 224, 224, 3)	0
block1_conv1 (Conv2D)	(None, 224, 224, 64)	1792
block1_conv2 (Conv2D)	(None, 224, 224, 64)	36928
block1_pool (MaxPooling2D)	(None, 112, 112, 64)	0
block2_conv1 (Conv2D)	(None, 112, 112, 128)	73856
block2_conv2 (Conv2D)	(None, 112, 112, 128)	147584
block2_pool (MaxPooling2D)	(None, 56, 56, 128)	0
block3_conv1 (Conv2D)	(None, 56, 56, 256)	295168
block3_conv2 (Conv2D)	(None, 56, 56, 256)	590080
block3_conv3 (Conv2D)	(None, 56, 56, 256)	590080
block3_pool (MaxPooling2D)	(None, 28, 28, 256)	0
block4_conv1 (Conv2D)	(None, 28, 28, 512)	1180160
block4_conv2 (Conv2D)	(None, 28, 28, 512)	2359808
block4_conv3 (Conv2D)	(None, 28, 28, 512)	2359808
block4_pool (MaxPooling2D)	(None, 14, 14, 512)	0
block5_conv1 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv2 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv3 (Conv2D)	(None, 14, 14, 512)	2359808
block5_pool (MaxPooling2D)	(None, 7, 7, 512)	0
flatten (Flatten)	(None, 25088)	0
fc1 (Dense)	(None, 128)	3211392
fc2 (Dense)	(None, 128)	16512
output (Dense)	(None, 3)	387

Total params: 17,942,979
Trainable params: 3,228,291
Non-trainable params: 14,714,688

FIGURE 4.9: Architectural Summary of Image Classification Model using Modified VGG-16

4.4 Matching Request To Offer

The tweets and severity measure obtained as the result of the previous text and image classification modules respectively, along with the predicted label are fed as input to this module. The severity measure of image associated with requests are used for prioritization. The mapping is done one offer to one request and one offer to many requests.

4.4.1 One to One Matching

The algorithm behind the one to one matching process is illustrated below :

```
Input: requests,offers,image_severity
Output: matched_tweets
maxm = threshold_value
for o ←offers do
    for r ←requests do
        measure = similarity(r,o);
        if measure ≥maxm then
            if abs(measure-maxm) ≤0.01 then
                matched_request ← max_severity(r, o);
            else
                no updation of matched request;
            end
        else
            continue;
        end
    end
    display(matched_request,o);
    remove_from_list(matched_request);
end
```

Algorithm 3: One to One Matching Algorithm

4.4.2 One to Many Matching

Since there could arise a situation wherein a single offer can satisfy multiple requests, one offer to many requests mapping is performed. This mapping is done by considering top five most similar requests for the current offer tweet based on similarity measure. These are further sorted based on the severity measure of the particular tweet's image. This prioritizes similar tweets.

```
Input: requests,offers,image_severity
Output: matched_tweets
maxm = threshold_value
for o ←offers do
    for r ←requests do
        measure = similarity(r,o);
        if measure ≥maxm then
            request_list ←r
        end
        top_5 = sort_desc(request_list,measure);
        matched_request = prioritize(top_5,image_severity);
    end
    display(matched_request,o);
end
```

Algorithm 4: One to Many Matching Algorithm

CHAPTER 5

IMPLEMENTATION RESULTS

In this section, the implementation results and their performance comparisons are presented in detail.

5.1 Live Tweet Extraction

Since the system operates on real-time tweets posted on Twitter by authenticated users, the trending tweets are extracted based on geographic location specified by WOE_ID i.e Where On Earth Identifier.

```
-----------------TRENDING TOPICS IN INDIA-----------------
#SoulSoothingMusicByStMSG
#AskKartik
#DancePlus4Finale
#MajesticVISWASAM25Days
#SochHack
Rishi Kumar Shukla
the pantu series
Alzarri Joseph
NAVRANGI RE
Mallikarjun Kharge
ऋषि कुमार शुक्ला
Newcastle
Delhi-NCR
Thakurnagar
Dalai Lama
Dance Plus 4
#TheVoiceTomorrow
#MrLocal
#CBIDirector
#FabricOfTheFuture
#TOTNEW
#CHEHUD
#LKGtrailer
#BengalWithModi
#earthquake
#KarsevakMassacre
#SmritiMandhana
#சிறப்புச்சம்பவம்ஒன்று
#designdekko
#NonStopJumlaSarkar
#BTSAtPVR
#rupaypvl
#HappyBirthdaySTR
#AnandTeltumbde
```

FIGURE 5.1: Trending Hashtags in India

```
#25daysofViswasam
#XUV300
#laffaire2019
#Thalaivar166
#ModiInBengal
#RJBalaji
---------------------------------------------------

earthquake
**** A Disaster has occured !!! ****

2019-02-02 15:28:00 1091719893307793408 Witribe Internet Truly Unlimited (Residential)
Device Activation : Rs. 2999 (One Month Free Internet)
Monthly 1399*
3 Days Money Back Guarantee
Same Day Delivery
#PMHazirHai
#earthquake
#NA91
#زردای_ڈاکو_نواز_چور
#ArmanLuni
Indonesia
Shadab Khan
Phil
DAIGO
SONGS {'hashtags': [{'text': 'PMHazirHai', 'indices': [162, 173]}, {'text': 'earthquake', 'indices': [174, 185]}, {'text': 'NA91', 'indices': [186, 191
2019-02-02 15:27:03 1091719655943598080 #Earthquake  M 2.5 - 11km N of Willow, Alaska https://t.co/V5cOn2WXlV {'hashtags': [{'text': 'Earthquake', 'ind
2019-02-02 15:26:07 1091719420756586497 #earthquake #BharatSeLeinGeAzadi #17thYoungLeadersSummit #تعمیر_ملت# زردای_ڈاکو_نواز_چور  Why you have to upskil
2019-02-02 15:25:36 1091719291739635712 00:25:03 Acceleation change of underground Iwate #Earthquake {'hashtags': [{'text': 'Earthquake', 'indices': [4
2019-02-02 15:25:21 1091719227646582784 12:25:03 Acceleation change of underground Iwate #Earthquake {'hashtags': [{'text': 'Earthquake', 'indices': [4
2019-02-02 15:24:14 1091718944791105537 Don't claim that your self made if I helped you throughout the way I was the oven nigga □□□ @WORLDSTAR @Kollege
2019-02-02 15:24:00 1091718887408914433 #Earthquake (#sismo) M3.2 strikes 63 km SW of San Antonio (#Chile) 21 min ago. More info: https://t.co/KtqNdxfF
2019-02-02 15:22:37 1091718540355387393 Check it out! uzair shah will create eve catching  whiteboard animation an... for $10 on
```

FIGURE 5.2: Extracted Tweets during Disaster

These trending hashtags are analysed to check for the presence of a disaster as shown in Fig 5.2.

5.2 Data Preprocessing

The textual content of the extracted tweets are then preprocessed. The tweets before and after the proprocessing step are depicted in Figures 5.3 and 5.4 respectively.

TIMESTAMP	TWEET_ID	TWEET_TEXT
2015-04-28 09:00:55	592976777447919616	Please save thousands of survivals of Nepal Earthquake. They are foodless, shelter less, even they dont have... http://t.co/e5L8Z4p4BL
2015-05-06 09:15:52	595879644127227904	Nidan to distribute rice, dal and oil and other groceries and tents for temporary shelter to Nepal earthquake... http://t.co/nS6hUc9qeV
2015-04-27 16:28:52	592727118766862336	RT @NRaule: Last night, people are searching for tent, at BICC area. No foods, no water. #earthquake #Nepal http://t.co/6IMSqiQxTc
2015-04-26 15:50:25	592355054323019776	RT @fullauri: can anyone we know pick the 2000 second hand tents from Sunauli and distribute it to the people in need in Nepal? #NepalQuake
2015-04-29 15:47:23	593441455764410369	RT @DDNewsLive: Earthquake toll can reach 10,000; Crisis looms over #Nepal due to shortage of basic amenities Full Story: http://t.co/FFn4C…
2015-04-28 06:31:32	592939185889214464	Trying to restart our work with no telephone and no internet at the office after devastating earthquake on... http://t.co/PS9U4vzXRg
2015-04-28 04:03:23	592901901479505920	#Nepal #Earthquake day four. Slowly in the capital valley Internet and electricity beeing restored . A relief for at least some ones
2015-04-29 17:06:49	593461448497500162	@KP24 Plz shout for help to the earthquake victims of Nepal. We need TENTS, lotts of TENTS. Homes demolished. Under empty sky as it rains
2015-04-26 09:25:59	592258310696501248	RT @Kazi_Australia: ⭑ #News • World Vision flies in help to Nepal: TENTS, medicine and hygiene packs are being flown in by World ... http:...
2015-04-28 16:00:58	593082485744881664	Nepal earthquake: Death toll crosses 5000; shortage of food, medicine, shelter - Zee News http://t.co/DCCuzkIiPZ
2015-04-30 11:00:36	593731671658090497	RT @ArtOfLivingUK: Nepal Earthquake Relief Update: The Art of Living volunteers continue offering food and medical supplies and... http://…
2015-04-29 11:33:04	593377453952913408	PLEASE HELP NEPAL EARTHQUAKE VICTIMS AND SEND CLOTHES, FOOD , MEDICINES
2015-04-28 18:06:20	593114034611757056	RT @GumberInsan: Earthquake in nepal. Plz snd food, clothes nd money to hlp people lik dera sacha sauda is doing http://t.co/uxxUclfvgM
2015-05-01 02:11:42	593960959582064640	@tarsem_insan Dera Sacha Saudaने नेपाल और बिहार में भेजी राहत सामग्री Watch On YouTube- https://t.co/SC4V2gUnr1
2015-04-30 09:44:25	593712499595153408	RT @unicefireland: Almost 1 million children need help in Nepal after the 7.8 earthquake. Please text 'CHILD' to 50300 to donate €4 now. ht…
2015-05-01 07:23:56	594039536079908865	नेपाल: भूकंप पीड़ित लूट रहे राहत सामग्री के ट्रक, 15 हजार के करीब मौतों की आशंका - Rajasthan... #World http://t.co/poGcL0PFI7
2015-04-27 16:53:32	592733327318188034	RT @ashim888: "@JackWilshere: Children are in danger #Nepal earthquake, please support to provide urgent help - http://t.co/7kwINfatZt PLS …
2015-04-28 07:00:51	592946562277482497	donate a dollar, nonperishable food, clothes, tents and raincoats. #Nepal #earthquake #quakeinnepal #prayfornepal https://t.co/leJrDs19xK
2015-04-29 12:41:53	593394771877433344	RT @Manmeet_kaurMK: Bangla Saheb Gurudwara, Delhi is sending 25,000 food packages daily for the 'Nepal' earthquake victims. #RealLions http…
2015-04-27 18:04:30	592751186152919042	RT @janeintheworld: Nepal women's groups need funds for pregnant & lactating mothers, sanitation, food, shelter. Please give http://t.co/CU…
2015-04-30 09:54:42	593715088348971008	People are in need for tents everywhere, we are failing to meet their demands #frustrating# nepal earthquake #scatteredreliefwork
2015-04-26 15:50:25	592355054323019776	RT @fullauri: can anyone we know pick the 2000 second hand tents from Sunauli and distribute it to the people in need in Nepal? #NepalQuake
2015-04-28 07:09:38	592948772767932416	PLEASE SHARE : NEPAL EARTHQUAKE: SHUDDHI is in Nepal. We urgently need your help to provide clean water,... http://t.co/HlDt2af9o8
2015-04-26 08:42:42	592247418374094848	RT @AsimBajwaISPR: To provide relief to EQ victims in Nepal,4 C-130 acs with 30 bedded hosp,Army Drs,special search&rescue teams, food item…

FIGURE 5.3: Tweets Before Preprocessing

TIMESTAMP	TWEET_ID	TWEET_TEXT
2015-04-28 09:00:55	592976777447919616	please save thousands of survivals of nepal earthquake they are foodless shelter less even they dont have
2015-05-06 09:15:52	595879644127227904	nidan to distribute rice dal and oil and other groceries and tents for temporary shelter to nepal earthquake
2015-04-27 16:28:52	592727118766862336	last night people are searching for tent at bicc area no foods no water earthquake nepal
2015-04-26 15:50:25	592355054323019776	can anyone we know pick the 2000 second hand tents from sunauli and distribute it to the people in need in nepal nepalquake
2015-04-29 15:47:23	593441455764410369	earthquake toll can reach 10000 crisis looms over nepal due to shoage of basic amenities full story
2015-04-28 06:31:32	592939185889214464	trying to resta our work with no telephone and no internet at the office after devastating earthquake on
2015-04-28 04:03:23	592901901479505920	nepal earthquake day four slowly in the capital valley internet and electricity beeing restored a relief for at least some ones
2015-04-29 17:06:49	593461448497500162	plz shout for help to the earthquake victims of nepal we need tents lotts of tents homes demolished under empty sky as it rains
2015-04-26 09:25:59	592258310696501248	news world vision flies in help to nepal tents medicine and hygiene packs are being flown in by world http
2015-04-28 16:00:58	593082485744881664	nepal earthquake death toll crosses 5000 shoage of food medicine shelter zee news
2015-04-30 11:00:36	593731671658090497	nepal earthquake relief update the a of living volunteers continue offering food and medical supplies and
2015-04-29 11:33:04	593377453952913408	please help nepal earthquake victims and send clothes food medicines
2015-04-28 18:06:20	593114034611757056	earthquake in nepal plz snd food clothes nd money to hlp people lik dera sacha sauda is doing
2015-05-01 02:11:42	593960959582064640	dera sacha sauda watch on youtube
2015-04-30 09:44:25	593712499595153408	almost 1 million children need help in nepal after the 78 earthquake please text child to 50300 to donate 4 now ht
2015-05-01 07:23:56	594039536079908865	15 rajasthan world
2015-04-27 16:53:32	592733327318188034	children are in danger nepal earthquake please suppo to provide urgent help pls
2015-04-28 07:00:51	592946562277482497	donate a dollar nonperishable food clothes tents and raincoats nepal earthquake quakeinnepal prayfornepal
2015-04-29 12:41:53	593394771877433344	bangla saheb gurudwara delhi is sending 25000 food packages daily for the nepal earthquake victims reallions http
2015-04-27 18:04:30	592751186152919042	nepal women is groups need funds for pregnant lactating mothers sanitation food shelter please give
2015-04-30 09:54:42	593715088348971008	people are in need for tents everywhere we are failing to meet their demands frustrating nepal earthquake scatteredreliefwork
2015-04-26 15:50:25	592355054323019776	can anyone we know pick the 2000 second hand tents from sunauli and distribute it to the people in need in nepal nepalquake
2015-04-28 07:09:38	592948772767932416	please share nepal earthquake shuddhi is in nepal we urgently need your help to provide clean water
2015-04-26 08:42:42	592247418374094848	to provide relief to eq victims in nepal4 c130 acs with 30 bedded hosparmy drsspecial searchrescue teams food item
2015-04-27 17:15:27	592738844581240834	mobile phones are not working no electricity no water in thamel nepal earthquake nepalearthquake nepalquakerelief

FIGURE 5.4: Tweets After Preprocessing

5.3 Classification

5.3.1 Text Classification

5.3.1.1 Training

The text classification model is trained as given in Section 4. The training results for variation 1 and variation 2 are given in Fig 5.5 and Fig 5.6 respectively.

```
In [46]: runfile('/home/kavya/preprocessing.py', wdir='/home/kavya')
Train on 1450 samples, validate on 622 samples
Epoch 1/10
1450/1450 [==============================] - 10s 7ms/step - loss: 0.6516 - acc: 0.6152 -
val_loss: 0.6014 - val_acc: 0.6720
Epoch 2/10
1450/1450 [==============================] - 6s 4ms/step - loss: 0.3691 - acc: 0.8614 -
val_loss: 0.4638 - val_acc: 0.7990
Epoch 3/10
1450/1450 [==============================] - 6s 4ms/step - loss: 0.1544 - acc: 0.9545 -
val_loss: 0.4764 - val_acc: 0.8006
Epoch 4/10
1450/1450 [==============================] - 6s 4ms/step - loss: 0.0760 - acc: 0.9814 -
val_loss: 0.5532 - val_acc: 0.7878
Epoch 5/10
1450/1450 [==============================] - 6s 4ms/step - loss: 0.0473 - acc: 0.9876 -
val_loss: 0.6559 - val_acc: 0.7926
Epoch 6/10
1450/1450 [==============================] - 6s 4ms/step - loss: 0.0361 - acc: 0.9869 -
val_loss: 0.5614 - val_acc: 0.7942
Epoch 7/10
1450/1450 [==============================] - 6s 4ms/step - loss: 0.0264 - acc: 0.9917 -
val_loss: 0.6771 - val_acc: 0.7701
Epoch 8/10
1450/1450 [==============================] - 6s 4ms/step - loss: 0.0190 - acc: 0.9931 -
val_loss: 0.6994 - val_acc: 0.7942
Epoch 9/10
1450/1450 [==============================] - 7s 5ms/step - loss: 0.0198 - acc: 0.9917 -
val_loss: 0.6765 - val_acc: 0.7942
Epoch 10/10
1450/1450 [==============================] - 6s 4ms/step - loss: 0.0142 - acc: 0.9938 -
val_loss: 0.7583 - val_acc: 0.7942
Training completed 100%
```

FIGURE 5.5: Training Result for Text Classification Model (Variation 1)

5.3.1.2 Accuracy Comparison

The testing accuracy of Model I is 79.42%. The changes that were made as per Table 4.1 led to the improvement in the overall accuracy of the model reaching as high as 85.37% testing accuracy.

The training vs testing accuracy of the two models are graphical represented in Figure 5.7.

```
4425/4425 [==============================] - 34s 8ms/step - loss: 0.3295 - acc: 0.8579 -
val_loss: 0.3815 - val_acc: 0.8284
Epoch 7/20
4425/4425 [==============================] - 33s 8ms/step - loss: 0.3126 - acc: 0.8649 -
val_loss: 0.4151 - val_acc: 0.8211
Epoch 8/20
4425/4425 [==============================] - 34s 8ms/step - loss: 0.2905 - acc: 0.8784 -
val_loss: 0.3930 - val_acc: 0.8248
Epoch 9/20
4425/4425 [==============================] - 34s 8ms/step - loss: 0.2687 - acc: 0.8879 -
val_loss: 0.3491 - val_acc: 0.8609
Epoch 10/20
4425/4425 [==============================] - 34s 8ms/step - loss: 0.2474 - acc: 0.8945 -
val_loss: 0.3412 - val_acc: 0.8591
Epoch 11/20
4425/4425 [==============================] - 33s 8ms/step - loss: 0.2323 - acc: 0.9037 -
val_loss: 0.3485 - val_acc: 0.8627
Epoch 12/20
4425/4425 [==============================] - 34s 8ms/step - loss: 0.2157 - acc: 0.9114 -
val_loss: 0.3488 - val_acc: 0.8690
Epoch 13/20
4425/4425 [==============================] - 36s 8ms/step - loss: 0.2013 - acc: 0.9164 -
val_loss: 0.3468 - val_acc: 0.8699
Epoch 14/20
4425/4425 [==============================] - 33s 7ms/step - loss: 0.1864 - acc: 0.9250 -
val_loss: 0.3531 - val_acc: 0.8699
Epoch 15/20
4425/4425 [==============================] - 33s 7ms/step - loss: 0.1766 - acc: 0.9281 -
val_loss: 0.4183 - val_acc: 0.8365
Epoch 16/20
4425/4425 [==============================] - 33s 8ms/step - loss: 0.1702 - acc: 0.9304 -
val_loss: 0.3806 - val_acc: 0.8582
Epoch 17/20
4425/4425 [==============================] - 35s 8ms/step - loss: 0.1471 - acc: 0.9412 -
val_loss: 0.4345 - val_acc: 0.8211
Epoch 18/20
4425/4425 [==============================] - 34s 8ms/step - loss: 0.1464 - acc: 0.9442 -
val_loss: 0.4411 - val_acc: 0.8482
Epoch 19/20
4425/4425 [==============================] - 33s 8ms/step - loss: 0.1354 - acc: 0.9458 -
val_loss: 0.4432 - val_acc: 0.8564
Epoch 20/20
4425/4425 [==============================] - 34s 8ms/step - loss: 0.1269 - acc: 0.9496 -
val_loss: 0.4629 - val_acc: 0.8537
```

FIGURE 5.6: Training Result for Text Classification Model (Variation 2)

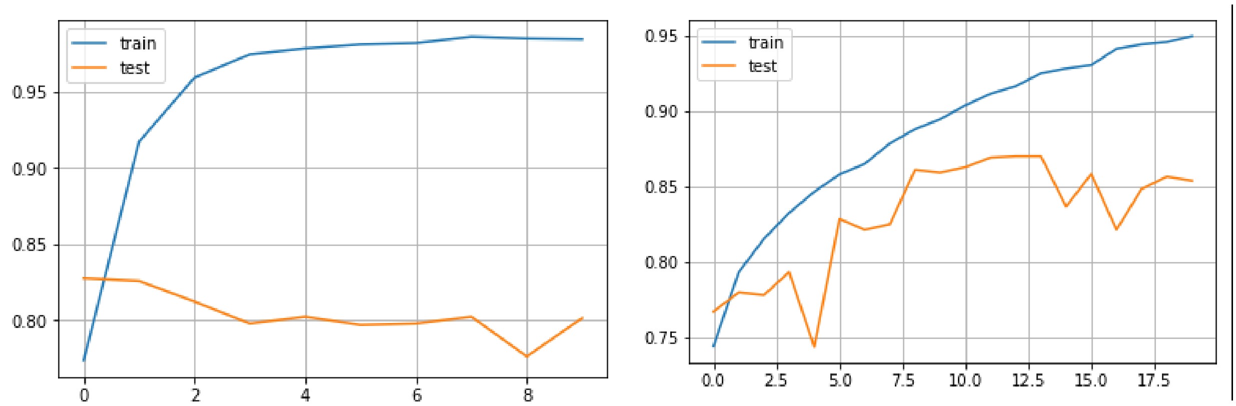

FIGURE 5.7: Comparison of Training and Testing Accuracy of LSTM Variations 1 And 2 respectively.

5.3.2 Image Classification

5.3.2.1 Training

```
Epoch 4/20
15258/15258 [==============================] - 58s 4ms/step - loss: 0.4367 - acc: 0.8324 - val_loss: 0.6106 - val_acc: 0.7722
Epoch 5/20
15258/15258 [==============================] - 58s 4ms/step - loss: 0.3971 - acc: 0.8445 - val_loss: 0.5715 - val_acc: 0.8016
Epoch 6/20
15258/15258 [==============================] - 58s 4ms/step - loss: 0.3619 - acc: 0.8597 - val_loss: 0.5730 - val_acc: 0.8149
Epoch 7/20
15258/15258 [==============================] - 58s 4ms/step - loss: 0.3260 - acc: 0.8724 - val_loss: 0.5814 - val_acc: 0.8207
Epoch 8/20
15258/15258 [==============================] - 58s 4ms/step - loss: 0.3030 - acc: 0.8784 - val_loss: 0.6282 - val_acc: 0.8045
Epoch 9/20
15258/15258 [==============================] - 58s 4ms/step - loss: 0.2772 - acc: 0.8919 - val_loss: 0.7361 - val_acc: 0.8018
Epoch 10/20
15258/15258 [==============================] - 58s 4ms/step - loss: 0.2576 - acc: 0.8987 - val_loss: 0.6445 - val_acc: 0.8076
Epoch 11/20
15258/15258 [==============================] - 58s 4ms/step - loss: 0.2387 - acc: 0.9081 - val_loss: 0.6995 - val_acc: 0.8052
Epoch 12/20
15258/15258 [==============================] - 58s 4ms/step - loss: 0.2296 - acc: 0.9076 - val_loss: 0.7331 - val_acc: 0.8102
Epoch 13/20
15258/15258 [==============================] - 58s 4ms/step - loss: 0.2097 - acc: 0.9174 - val_loss: 0.7743 - val_acc: 0.7733
Epoch 14/20
15258/15258 [==============================] - 58s 4ms/step - loss: 0.1993 - acc: 0.9215 - val_loss: 0.7778 - val_acc: 0.7992
Epoch 15/20
15258/15258 [==============================] - 58s 4ms/step - loss: 0.1891 - acc: 0.9286 - val_loss: 0.7940 - val_acc: 0.8005
Epoch 16/20
15258/15258 [==============================] - 58s 4ms/step - loss: 0.1840 - acc: 0.9273 - val_loss: 0.8110 - val_acc: 0.7748
Epoch 17/20
15258/15258 [==============================] - 58s 4ms/step - loss: 0.1729 - acc: 0.9322 - val_loss: 0.7839 - val_acc: 0.8021
Epoch 18/20
15258/15258 [==============================] - 58s 4ms/step - loss: 0.1599 - acc: 0.9353 - val_loss: 1.0631 - val_acc: 0.7785
Epoch 19/20
15258/15258 [==============================] - 58s 4ms/step - loss: 0.1575 - acc: 0.9385 - val_loss: 1.0406 - val_acc: 0.8081
Epoch 20/20
15258/15258 [==============================] - 58s 4ms/step - loss: 0.1522 - acc: 0.9401 - val_loss: 0.9965 - val_acc: 0.7840
Training time: -1167.6329910755157
3815/3815 [==============================] - 14s 4ms/step
[INFO] loss=0.9965, accuracy: 78.4010%
```

FIGURE 5.8: Training Result of Image Classification Model(Modified VGG-16)

5.3.3 Merging of Text and Image Classification Outputs

tweet_id	tweet_text	result
869918891664977921	iran news us foreign aid arrives in as sri lanka flood toll exceeds 200	offer
869950122972635136	floodsl they still need our help flood2017 srilanka floodreliefIka photo courtesy shehan gunasekara	request
869954479524691968	open our hands for them along with prayer	offer
869957461993635840	indian navy carries out relief operations in floodhit sri lanka	offer
869962038214131712	sri lankas flood survivors at risk of dengue disease aid workers	none
869984832364756992	srilanka appeals for help as floods cripple water supply	request
869988473419309059	misery in the rohingya refugee camps after cyclone mora walls and roofs blown away bangladesh	request
869967714948849664	floodsl 200 deaths reported due to floods and landslides in sri lanka lka helpsrilanka	offer
870079994306871296	your small breakfast amount can change their condition support to them	request
869968240956420096	this guy is building a phone charger with 40 charge ports for flood victims floodsl	offer
869972354004393987	pak navy continues humanitarian assistance and disaster relief operations in flood stricken sri lanka respect	offer

Text_classification

tweet_id	severity
869918891664977921	1
869950122972635136	1
869954009963970560	1
869954479524691968	2
869957051547435008	0
869957461993635840	2
869962038214131712	2
869963334401052673	2
869967714948849664	2
869968240956420096	2
869972354004393987	1

Image_classification

Merging based on tweet_id

tweet_id	tweet_text	result	severity
869918891664977921	iran news us foreign aid arrives in as sri lanka flood toll exceeds 200	offer	1
869950122972635136	floodsl they still need our help flood2017 srilanka floodreliefIka photo courtesy shehan gunasekara	request	1
869954479524691968	open our hands for them along with prayer	offer	2
869957461993635840	indian navy carries out relief operations in floodhit sri lanka	offer	2
869962038214131712	sri lankas flood survivors at risk of dengue disease aid workers	none	2
869984832364756992	srilanka appeals for help as floods cripple water supply	request	1
869988473419309059	misery in the rohingya refugee camps after cyclone mora walls and roofs blown away bangladesh	request	0
869967714948849664	floodsl 200 deaths reported due to floods and landslides in sri lanka lka helpsrilanka	offer	2
869968240956420096	this guy is building a phone charger with 40 charge ports for flood victims floodsl	offer	2
870079994306871296	your small breakfast amount can change their condition support to them	request	2
869972354004393987	pak navy continues humanitarian assistance and disaster relief operations in flood stricken sri lanka respect	offer	1

FIGURE 5.9: Merging of Text and Image Classification Outputs

5.4 Matching of Request to Offer

The output of the one-to-one matching in the form of (offer,request) pair is shown in Figure 5.10:

```
-----------------------------------------------------------------------------------------------------------------------------
TWEET_ID             |   TWEET_TEXT
-----------------------------------------------------------------------------------------------------------------------------
595879644127227904   |   nidan to distribute rice dal and oil and other groceries and tents for temporary shelter to nepal earthquake
593743633347530752   |   need foodwatertent and medicine for nepal earthquake survivorsgive to nepal relief fund
                     |   MATCHING SIMILARITY : 0.8662994966798735
-----------------------------------------------------------------------------------------------------------------------------
592901901479505920   |   nepal earthquake day four slowly in the capital valley internet and electricity beeing restored  a relief for at least
 some ones
592929862832099328   |   acute crisis of water power  medical facilities in nepal after earthquake this and more water news from last week
                     |   MATCHING SIMILARITY : 0.8935848985379719
-----------------------------------------------------------------------------------------------------------------------------
592258310696501248   |    news  world vision flies in help to nepal tents medicine and hygiene packs are being flown in by world
595629811609051136   |   relief goods for nepal earthquake victims held up at customs un says nepal say is  we need grains salt and sugar
                     |   MATCHING SIMILARITY : 0.8890604012703814
-----------------------------------------------------------------------------------------------------------------------------
593731671658090497   |   nepal earthquake relief update the art of living volunteers continue offering food and medical supplies and
593927918645940224   |   nepal earthquake urgent need for water sanitation and food nepalearthquake
                     |   MATCHING SIMILARITY : 0.9184961080436519
-----------------------------------------------------------------------------------------------------------------------------
593960959582064640   |   dera sacha sauda        watch on youtube
593240387453472768   |   5th dayno electricity unable to charge mobile continuous scarcity of water diarrhoea problem in kidsktm life afte
                     |   MATCHING SIMILARITY : 0.8015267247558764
-----------------------------------------------------------------------------------------------------------------------------
594039536079908865   |           15        rajasthan world
*** NO MATCH ***
-----------------------------------------------------------------------------------------------------------------------------
593394771877433344   |   bangla saheb gurudwara delhi is sending 25000 food packages daily for the nepal earthquake victims reallions
593490208475209728   |   nepal women is groups need funds for shelter sanitation food pregnant  lactating mothers give now
                     |   MATCHING SIMILARITY : 0.9054030543996601
-----------------------------------------------------------------------------------------------------------------------------
592247418374094848   |   to provide relief to eq victims in nepal4 c130 acs with 30 bedded hosparmy drsspecial searchrescue teams food item
592712844451434496   |   fight for food water and shelter among nepalese victims after 3 days long earthquake in nepal
                     |   MATCHING SIMILARITY : 0.8824532292349131
-----------------------------------------------------------------------------------------------------------------------------
```

FIGURE 5.10: One-to-One Mapping of Offer to Request

NOTE: In each matched set, the first line indicates the offer along with tweet_id and the second one represents the request.

The output of the one-to-many matching in the form of (offer,[request1,request2,...]) pair is shown in Figure 5.11 :

```
-------------------------------------------------------------------------------------------------------------------------------
TWEET_ID            |   TWEET_TEXT
-------------------------------------------------------------------------------------------------------------------------------
OFFER
595879644127227904  nidan to distribute rice dal and oil and other groceries and tents for temporary shelter to nepal earthquake
MATCHED REQUESTS
592355054323019776  can anyone we know pick the 2000 second hand tents from sunauli and distribute it to the people in need in nepal nepalquake
593441455764410369  earthquake toll can reach 10000 crisis looms over nepal due to shortage of basic amenities full story
593114034611757056  earthquake in nepal plz snd food clothes nd money to hlp people lik dera sacha sauda is doing
592946562277482497  donate a dollar nonperishable food clothes tents and raincoats nepal earthquake quakeinnepal prayfornepal
592751186152919042  nepal women is groups need funds for pregnant  lactating mothers sanitation food shelter please give
-------------------------------------------------------------------------------------------------------------------------------
OFFER
592901901479505920  nepal earthquake day four slowly in the capital valley internet and electricity beeing restored  a relief for at least some ones
MATCHED REQUESTS
592727118766862336  last night people are searching for tent at bicc area no foods no water earthquake nepal
593441455764410369  earthquake toll can reach 10000 crisis looms over nepal due to shortage of basic amenities full story
593082485744881664  nepal earthquake death toll crosses 5000 shortage of food medicine shelter  zee news
593590429670514688  google news  nepal earthquake homeless urgently need tents death toll above 5200  cnn
595461399679246336  queue waiting their turn to have water at pulchwok lalitpur near to plan office as earthquake has damaged water
-------------------------------------------------------------------------------------------------------------------------------
OFFER
592258310696501248   news world vision flies in help to nepal tents medicine and hygiene packs are being flown in by world
MATCHED REQUESTS
592727118766862336  last night people are searching for tent at bicc area no foods no water earthquake nepal
592355054323019776  can anyone we know pick the 2000 second hand tents from sunauli and distribute it to the people in need in nepal nepalquake
593441455764410369  earthquake toll can reach 10000 crisis looms over nepal due to shortage of basic amenities full story
593461448497500162  plz shout for help to the earthquake victims of nepal we need tents lotts of tents homes demolished under empty sky as it rains
593082485744881664  nepal earthquake death toll crosses 5000 shortage of food medicine shelter  zee news
-------------------------------------------------------------------------------------------------------------------------------
```

FIGURE 5.11: One-to-Many Mapping of Offer to Requests

NOTE: In each matched set,the first line indicates the offer along with tweet_id and the following line represents the requests.

5.5 Testing

The proposed system was tested for the FIRE 2017[4] IRMiDis dataset and an accuracy of around 75% was attained as shown in Figure 5.12.

```
------------------------------------------------------------
Correct Predictions |   232
Total Predictions   |   315
Accuracy            |   73.65079365079366
------------------------------------------------------------
```

FIGURE 5.12: Testing of the Proposed System

CHAPTER 6

CONCLUSION AND FUTURE WORK

In this thesis, we have presented an automatic tool for matching request and offer tweets that works on real-time, multimodal Twitter data. The real-tine aspect of the proposed system proves it to be competent enough to handle huge velocity of disaster-related data. At the same time, the multimodal aspect helps in handling variety of disaster-related data by taking the rich information from images into consideration. The use of state-of-the-art deep learning techniques for both the text and image classification have proved to be efficient.

In future, we plan to modify the system to handle multiple disasters at the same time and tweets containing only imagery content. Also, to enhance the accuracy of the text and image classification models by increasing the training dataset. In addition to that, we also look forward to improve the matching algorithm to be more powerful. This would result in a mapping algorithm that takes into account the quantity/capacity of supplies, whether the entity that demands or supplies is an individual or organization, identifying immediate requests, etc and match them accordingly. We also have an idea of extending the existing proposed system to handle tweets with video and audio content. This would give us a deeper understanding of the aftermath of a disaster and thus, help in effective crisis management.

Finally, we also plan to expand our system to handle multiple languages and not just be limited to the English language tweets, though it contributes to more than one third of the worldwide tweets.

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