A Comparative Study on Disaster Detection from Social Media Images using Deep Learning

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Abstract: The availability of images of events almost in real-time on social media has a prospect in many application developments. A humanitarian technology for disaster type and level assessment can be developed using the images and video available on social media. In this paper, we investigate the potential use of various available deep learning techniques to develop such an application. For our research, based on the use of publicly available image data, we have started collecting disaster images from various sources from South Asia. We created the South Asia Disaster (SAD) image dataset containing 493 images from various online news portals. Using the Keras as our framework to run our models: Visual Geometry Group (VGG-16 and VGG-19), Inception-V3 and Inception-ResNet-V2 (ResNet: Residual Network). However, to boost up the training speed, we dropped the fully connected layer and added a small, fully connected model. To identify the five different disasters: fire disaster, flood disaster, human disaster, infrastructure disaster, natural disaster; our proposed method with VGG-16 model's recognition accuracy was 83.37%, which is the highest accuracy on the SAD dataset.

Keywords: Disaster image, humanitarian technology, standard disaster dataset, Convolutional Neural Network, VGG-16, VGG-19, Inception-V3, Inception-ResNet-V2, Keras model.

1. Introduction

Bangladesh is one of the most vulnerable countries that suffer from huge climate change, as well as disasters. Bangladesh's flat topography, low-lying and climatic features are responsible for natural disasters, i.e., floods, cyclones, droughts, and earthquakes Moreover, its population density and socioeconomic environments make it highly susceptible to many human-made hazards that include fire, building collapse, infrastructural damage, road accident, etc. Also, there are other disasters happening like infrastructure or non-natural disasters. Day after day, people are suffering from different kinds of disasters (e.g., Fire incidents in Chawk Bazar, Banani Fire incident). These incidents which happened in March 2019 were featured by some newspapers such as the famous online news portal Dhaka Tribune [12], The Daily Star [13], etc. It is crucial in times of crisis that how emergency response workers reach all those affected promptly. It would be great to have a system that would raise an alert and determine the degree of damage of any disaster and inform the appropriate authorities based on the automated analysis of the image data that are almost all the time available in real-time on various social media. There has been some effort along this direction.

Rizk et al. [1] proposed a multi-modal approach to automate crisis data analysis using machine learning. The proposed multi-modal two-stage framework relies on computationally inexpensive visual and semantic features to analyze Twitter data. Level I (one) classification consists of training classifiers separately of semantic descriptors and combinations of visual features. These classifiers' decisions are aggregated to form a new feature vector to train the second set of classifiers in Level II (two) classification. In this second classification phase, two approaches are compared: score learning and majority vote.

In [2] presents the algorithms that CERTH team deployed to tackle disaster recognition tasks. Deep Convolutional Neural Network (DCNN), DBpedia Spotlight and combMAX were implemented to tackle DIRSM. The model GoogleNet was used to train on 5055 ImageNet concepts.

Giannakeris et al. [3] presented a novel warning system framework for detecting people and vehicles in danger. The proposed framework provides a near real-time localization solution for detecting and scoring severity and safety levels of people and vehicles in flood and fire images. They chose to fine-tune the pre-trained parameters of the VGG-16 on Places365 dataset to leverage useful distinctions between various visual clues that relate to generic scenery images. Their Initial 3F-emergency dataset is composed of 6K images from Flickr.

Alam et al. [4] proposed a work where their Image Filtering module employs deep neural networks and perceptual hashing techniques to determine whether a newly-arrived image is relevant for a given disaster response context. To train the relevancy filter, 3,518 images were randomly selected from the severe and mild categories. They adopted a transfer learning approach where they have used the VGG-16 network pre-trained on ImageNet data.

Mouzannar et al. [5] proposed a multimodal deep learning framework to identify damage related information from social media posts. This framework combines multiple pretrained unimodal convolutional neural networks that extract features from raw texts and images separately. The inception convolutional neural network (CNN) model was adopted, which was pre-trained on ImageNet to process images, and for words, they used a pre-trained word embedding model to process the texts. The framework was evaluated on a homegrown labeled dataset of multimodal social media posts.

In the paper [6], images posted on social media platforms during natural disasters to determine the level of damage caused by the disasters are analyzed. In this study, Imran et al. used the VGG-16 network trained on the ImageNet dataset.

They collected data from the Web (such as Typhoon Ruby, Hurricane Matthew, Nepal Earthquake, etc.) and made their dataset. They ran tests on their training sets, and the highest accuracy they achieved was when they combined their Google, Ruby and Matthew datasets.

In this research paper, we propose a deep learning-based method to automate the effective extraction of information from social media posts to direct relief resources efficiently. Since posts on social media contain text, photos, and videos, we are performing a deep learning framework for multimodal identification of damage-related information. Also, our objective is to collect and work with South Asian disaster images, which include disaster images of Bangladesh and similar countries.

2. Methodology

Our proposed system uses Keras as a framework to implement our models and modified deep learning algorithms to classify five different types of disaster images. And for all deep learning-based methods, data is the most important component. The reason for using Keras is that Keras is easy to use and very flexible. It supports the models we used for our paper. Compared to other neural network API Keras is light-weighted and very user-friendly. Keras is consistent and simple yet very powerful thanks to its Model and Sequential APIs, and hence, it helps create very complex neural networks in a matter of minutes. Another main reason for us to use Keras is that it is very popular, and Keras development is backed by key companies in deep learning ecosystem [14].

2.1. Dataset Description

Standard database is a prerequisite for better model creation [15]. The main issue using a deep learning system for classification is a well defined and diversified dataset. For this experiment, we collected the images from [11]. There are six different damage categories; they are: Fire damage, Flood damage, damage infrastructure, damage nature, Human damage, and Non-damage. There is a total of 5885 images, and the total number of images for each category is given in Table 1.

Table 1. Distribution of the number of disaster images for each class from [11] Dataset

Categories	Number
Fire damage	349
Flood damage	385
Damage Infrastructure	515
Damage nature	1418
Human damage	240
Non-damage	**2972**
Total	**5885**

The fire disaster images contain fire elements, smoke, and burning objects and burned objects. Flood disaster images contain a huge volume of water, objects underwater and objects submerged in water. Infrastructure disaster images contain collapsed buildings, rusted, and damaged objects. Nature disasters contain broken trees, buildings, and roads caused by earthquake or cyclone. Human disaster image contains bleeding, burned face, torturing people, and human damaging the environment. Non – disaster images contain products, cosmetics, books, human models, and people eating food. Some sample images from the [11] data set are given in Fig. 1. From Table 1, we can observe that Non-damage has the highest number of images, 2972 than other classes, the lowest number of images are human damage 240. Damage nature has the second-highest number of images 1418. Other classes have an adjacent number of images.

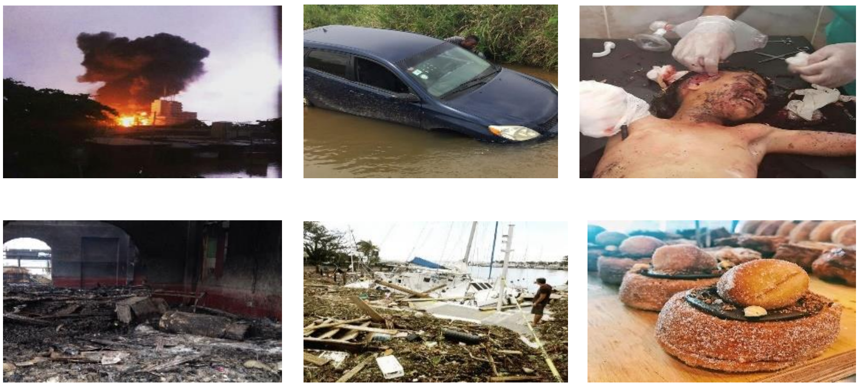


Fig. 1. Sample images from [11] Dataset (left-right): fire disaster, flood disaster, human disaster, infrastructure disaster, natural disaster, and non-disaster[1].

In the sample images note that the images are from mostly from outside South Asia. We intend to implement our system for Bangladesh and to check the performance on the native data, and we collected a small data set for this project. We are calling it, **SAD (South Asian Disaster)** image dataset. We have collected 493 data, and class-wise distribution can be found in Table 2.

Table 2. Distribution of the number of disaster images for each class from SAD Dataset

Categories	Number
Fire damage	82
Flood damage	82
Damage Infrastructure	65
Damage nature	73
Human damage	81
Non-damage	**110**
Total	**493**

[1] https://archive.ics.uci.edu/ml/datasets/Multimodal+Damage+Identification+for+Humanitarian+Computing

In Fig. 2, we gave samples of the SAD image dataset. Images were collected from online news portal, social news network, independent news organization, and online benefactor for people. We got 32 images from each online news portal such as The Times of India, The Hindu and Indian express. 32 images are collected from the UN news (news portal), 32 images from World Bank (online benefactor for people), 32 images from Rappler (social news network), 100 images from BBC (online news portal), 100 images from Fox news (online news portal) and rest from Al Jazeera (independent news organization). Visual Comparison among images from Fig. 1 and Fig. 2 it is clear that there are differences in perception of similar classes.

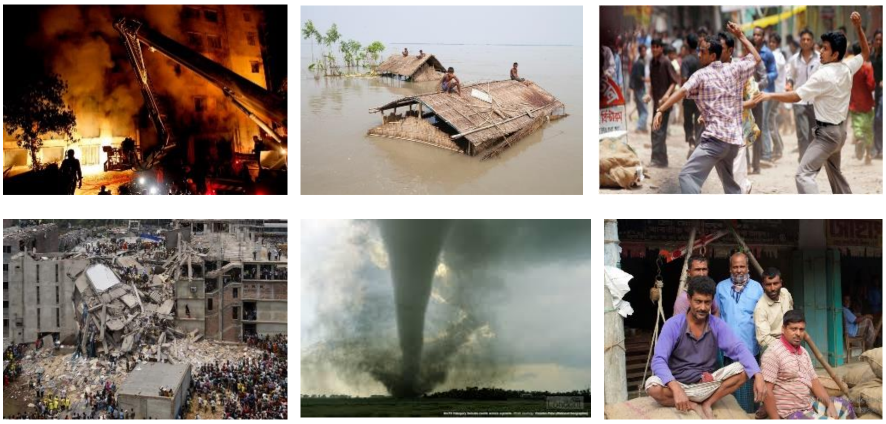


Fig. 2. Sample images from SAD image dataset (left-right): fire disaster, flood disaster, human disaster, infrastructure disaster, natural disaster, and non-disaster

2.2. Convolutional Neural Networks (CNNs)

CNNs have shown state-of-the-art efficiency in a multitude of computer vision challenges, including image classification and retrieval, object detection, and segmentation of images [10]. A typical CNN comprises of various processing layers, including convolution, max pooling, and fully connected layers. These layers are cascaded in a way that one layer's output becomes the next layer's input. A set of kernels are introduced to the input information to produce characteristic maps at each convolution layer [10].

Our study is mainly based on performing different types of experiments with different models on our SAD dataset and [11] dataset and compare and analyze their results. To perform our experiments, we have decided to use four models from three CNN families: Virtual Geometry Group (VGG) [8], Inception [9] by GoogLeNet and Inception Residual Network (ResNet) [7] by Microsoft. Our objective is to compare results; hence, we have decided to compare the results of different CNN families' model as their architectures are different from one another. The VGG architecture is deep, using only 3x3 convolutional layers stacked on top of each other, which increase depth. Volume size is reduced by max pool layer. It has cascaded convolution max-pool layers [8]. The Inception architecture, on the other hand, is “wider” rather than “deep” like the VGG architecture. The architecture typically consists of filters of 3 different sizes: 1x1, 3x3 and 5x5. After max-pooling, the outputs are concatenated and sent to the next inception module. The newer version of the architecture has an extra added 1x1 convolution before the 3x3 and 5x5 convolutions for cost-effectiveness [9]. One of the most popular CNN family in the present is the ResNet family by Microsoft. This architecture goes deeper than the VGG architecture with nodes having stems of different Inception Modules [7]. In [3] and [6] VGG-16 CNN model was implemented. The [5] Inception-V3, Inception-V4, VGG-16, and Inception-Resnet-V2, for disaster image classification. For our problem, we used VGG-16, VGG-19, Inception-V3, and Inception-ResNet-V2.

Visual Geometry Group (VGG) [8]: The VGG nets were originally designed to detect and recognize objects in images. VGG Nets proved to be efficient in the identification of objects in still pictures. VGG is a very profound model that significantly enhanced a wide variety of visual recognition functions, including detecting objects, semantic segmentation, picture captioning, and recognition of the action on video. VGG-16 has three fully connected layers follow a stack of convolutional layers, and the final layer is the softmax layer. It has a total of 16 layers; all hidden layers are equipped with rectification. VGG-19 model is very similar to the VGG-16 model. The main difference between VGG-16 and VGG-19 is that the VGG-19 has 19 layers instead of 16.

Inception [9]: Though, VGG Net has architectural simplicity and convincing features; this comes at a high price of relatively large computation time to evaluate the network. Inception architectures of GoogLeNet were intended to perform well even under rigorous memory and computer budget limitations. Inception's computational cost is also much smaller than the VGG Net. This made it possible to use Inception networks in large-data situations where large amounts of data required to be processed at a reasonable price or where memory or computing capability are inherently restricted. Inception-v1 has nine inception modules stacked linearly, and 27 layers deep, including pooling layers. In Inception-V2 the 5x5 convolution was factorized to two 3x3-convolution operations to improve computational speed and reduce computational expense. The Inception-V3 (INv3) is 42 layers deep; however, the computation is only about 2.5 times more than Inception-v1 and much more efficient than VGG Net.

Inception-ResNet-V2 [7]: Inception-ResNet-V2 (INRv2) is a 164 profound layer deep neural network that can classify pictures into 1000 categories of objects. Inception-ResNet-V2 has introduced residual connections that add the output of the convolution operation of the inception module to the input. For residual addition to work, the input and output after convolution must have the same dimensions. The pooling operation inside the main inception modules was removed to be replaced by the residual connections. To increase stability, the residual activations were scaled by a value within 0.1 to 0.3 range. It was found that Inception-ResNet models were able to achieve higher accuracies at a lower number of epochs.

The models that we are using for our experiment are: VGG-16, VGG-19, Inception-V3, and Inception-ResNet-V2. In Table 3, a comparative view of the number of parameters of all four above mentioned CNN models is given. However, we also implemented a small model and added that at the end of each of the models mentioned above, this is done by dropping the convolutional fully connected layer at the end. The reason for adding this small model is to speed up the training process.

In Fig. 3 we gave the schematic view of the models used. We have used relu activation on the 512 dense layers and also on the 256 dense layers so that all the layers are connected to each other. And then we used dropout, and it helps reduce over-fitting, by preventing a layer from seeing twice the same pattern. In the end, we used six dense layers because we have six classes. As optimizer we used Adam, and as loss function, sparse categorical cross-entropy is used

Table 3. Parameters of the models

Models	Parameters
VGG 16	138 Million
VGG 19	144 Million
Inception-V3	23 Million
Inception-ResNet-V2	54 Million

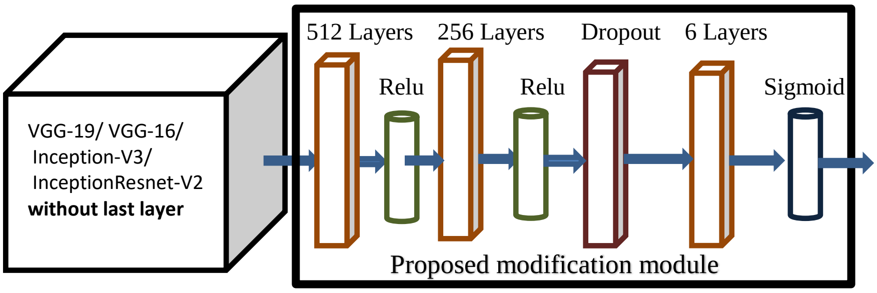


Fig.3. Schematic view of the proposed deep neural model

3. Experimental Setup

Images are usually of different size as they are collected from non-restricted sources. To feed them into the deep neural networks, they were resized to 150 by 150 pixels. For training the networks 50 epochs have been used, epoch means training the whole dataset in one cycle; however, it takes a lot of space in the memory. Therefore, the dataset is divided into batches to train. The batch size 11 and 12 are used for [11] training and testing dataset, respectively. For SAD dataset the batch size is 29 for the whole dataset. To run this experiment, we are using Intel core i5 processor and 8 GB DDR4 ram. The experiments that we are performing are:

1) **Experiment 01:** Cross-validation performance measure while training the CNNs with [11] dataset testing them on [11] dataset. Table 4 shows the results of this experiment.

2) **Experiment 02:** Performance measure while training with 100% [11] dataset and test with 100 % SAD dataset. Table 5 shows the results of this experiment

3) **Experiment 03:** Cross-validation performance measure while training with the 100% [11] dataset plus 60% of the SAD dataset and test with the remaining 40% of the SAD dataset. Table 6 shows the results of this experiment.

In Table 4, note that all four classifiers perform in the same range on average. However, different classifiers show slightly higher classification accuracy class of disaster.

Table 4. Cross-validation average performance of only [11] dataset

	Precision (%)				**Recall (%)**				**Accuracy(%)**			
	VGG19	**VGG16**	**INv3**	**INRv2**	**VGG19**	**VGG16**	**INv3**	**INRv2**	**VGG19**	**VGG16**	**INv3**	**INRv2**
Fire damage	63.31	58.74	**64.44**	58.22	68.00	67.33	67.96	**75.66**	95.51	95.62	95.72	**96.08**
Flood damage	**59.40**	51.63	41.93	51.12	54.82	60.64	**63.32**	63.12	93.92	**94.37**	93.91	94.25
Human damage	57.63	**59.11**	49.92	56.00	**71.21**	61.32	69.00	69.23	**97.07**	96.54	96.82	96.79
Damage Infrastructure	**70.92**	70.12	63.33	69.84	65.13	63.55	**67.66**	67.16	83.87	83.04	83.54	**84.33**
Damage Nature	37.75	47.00	48.10	**49.33**	**52.95**	51.00	47.91	50.94	**91.28**	91.13	90.40	91.06
Non-damage	83.52	82.71	85.55	**85.82**	**83.25**	83.13	79.84	81.83	**83.65**	82.91	81.79	82.60
Average	62.08	61.55	**67.20**	61.72	65.89	64.50	65.94	**67.99**	**90.88**	90.60	90.36	90.85

In Table 5, the first issue to note is that, as we test the classifiers trained with [11] dataset and test with our SAD dataset, the accuracy reduces by about 7%. This means that the [11] dataset does not contain well distributed and diverse data from all demography but the SAD dataset is different from [11] dataset (Fig. 4). Something very noticeable in this experiment is that the precision for human damage is significantly low for all classifiers (Fig. 1 and Fig. 2). This would mean that identifying human damage by a deep neural net trained with [11] dataset only is very difficult. VGG16 is an older version of the deep neural network; however, the overall accuracy of this classifier is slightly higher than other models for experiment 2.

In experiment 3, we added 60% of the SAD data with the [11] dataset, and it shows the improvement in performance. In Table 6, note that the precision of human damage improves. Moreover, accuracy is also increased. It suggests that if the networks can be trained with significantly large and diverse data, performance will increase with the same network setup.

Table 5. Performance of training with 100% [11] dataset and testing with 100% SAD dataset

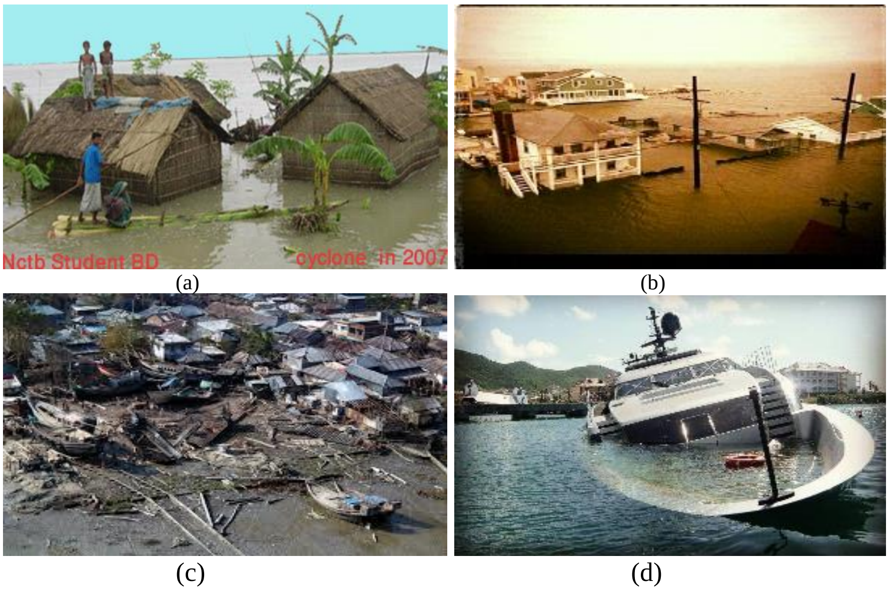
	Precision (%)				Recall (%)				Accuracy(%)			
	VGG19	VGG16	INv3	INRv2	VGG19	VGG16	INv3	INRv2	VGG19	VGG16	INv3	INRv2
Fire damage	46.33	59.73	**60.92**	37.83	97.44	83.11	81.92	100	90.87	**91.28**	**91.28**	89.66
Flood damage	45.12	**59.73**	46.33	43.93	74.02	62.83	80.52	75.00	88.24	87.42	**89.25**	88.24
Human damage	6.15	9.23	9.23	**10.73**	44.44	33.33	35.33	43.71	**86.61**	85.60	85.50	86.41
Damage Infrastructure	**82.22**	75.33	79.52	68.52	**32.11**	36.63	26.92	30.11	71.60	77.08	64.91	**71.81**
Damage Nature	30.83	32.12	17.31	**51.82**	56.81	54.23	51.82	51.22	**84.79**	84.38	83.77	83.98
Non-damage	**80.00**	71.82	61.83	70.00	53.71	**56.44**	54.44	51.34	80.12	**81.34**	79.92	78.51
Average	48.44	**51.32**	45.85	47.13	**59.75**	54.42	55.15	58.56	83.70	**84.51**	82.43	83.10

Table 6. Cross-validation performance of training with 100% [11] dataset plus 60% SAD dataset, and testing with 40% SAD dataset

	Precision (%)				Recall (%)				Accuracy(%)			
	VGG19	VGG16	INv3	INRv2	VGG19	VGG16	INv3	INRv2	VGG19	VGG16	INv3	INRv2
Fire damage	**72.22**	66.66	48.55	69.66	96.00	91.66	88.81	**100**	**94.95**	93.43	90.40	94.68
Flood damage	34.44	53.11	40.66	40.61	**84.63**	77.33	81.33	65.00	88.38	**89.90**	88.89	85.11
Human damage	17.43	**26.12**	8.69	21.72	36.44	35.32	**66.66**	38.55	86.87	85.86	**88.89**	84.04
Damage Infrastructure	**87.81**	78.82	84.81	78.73	39.22	**44.12**	40.51	40.00	75.25	**79.80**	79.77	70.74
Damage Nature	23.33	26.63%	**33.33**	23.33	**87.54**	50.00	45.55	50.00	**87.88**	84.85	83.84	86.17
Non-damage	80.81	78.71	**87.22**	76.52	56.73	**61.66**	58.62	57.12	80.81	**83.33**	82.32	76.06
Average	52.67	**55.01**	50.54	51.76	**66.76**	60.02	63.58	58.45	85.69	**86.20**	85.68	82.80

Comparing table 4 and 5, the accuracy dropped around 7% when preforming the second experiment. The reason for this drop of accuracy maybe for some specific class, there is significant between [11] and SAD dataset. In Fig. 4 we observe that SAD flooding disaster and nature disaster is different than other countries flooding disaster and natural disaster.

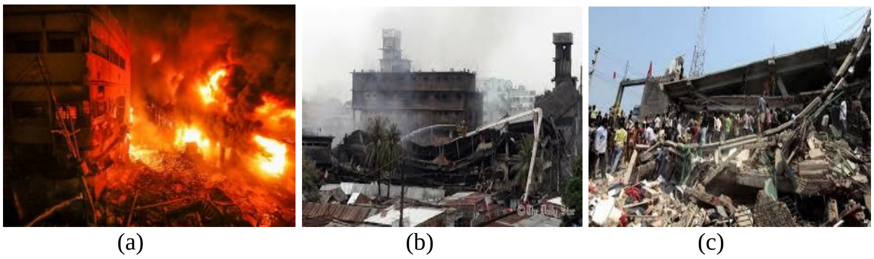
In Fig. 5 we provide some images associated with fire class, here we observed that there are two types of images: During fire disaster and after a fire disaster. In Fig. 5 not that during fire disaster and after fire disaster images are visually very distinctive. The difference is, in one has fire element, and smoke in it and the other one is all black, and there are ashes. Visually we ourselves are confused between the middle image (after fire disaster) and the right image (damaged infrastructure). Thus, the deep networks are also sometimes confused with after fire image and infrastructure disaster image.



(a) (b)

(c) (d)

Fig. 4. (Left – Right; Top-bottom) (a) SAD Flood damage; (b) Other Countries Flood damage; (c) SAD Damage Nature; (d) Other Countries Damage Nature



(a) (b) (c)

Fig. 5. (Left - Right) (a) During Fire damage; (b) After Fire damage; (c) Damage Infrastructure.

In Fig. 6, we provide some more images that are misclassified by our system.
(a) After fire damage classified as Damaged Infrastructure; (b) Is an actual infrastructural damage training image; (c) Another after fire damage classified as flood damage; in the image (d) the black and white floor and books floating resembles the state of the floor of (c), and in (e) the training flood image does not really look like a flood image, but there are pipes appearing in it which also appears in test image (c). We believe that some of the fire test images were classified as flood and infrastructure by Inception-V3 and Inception-ResNet-V2 models, because, the test image does not contain any fire object in them.

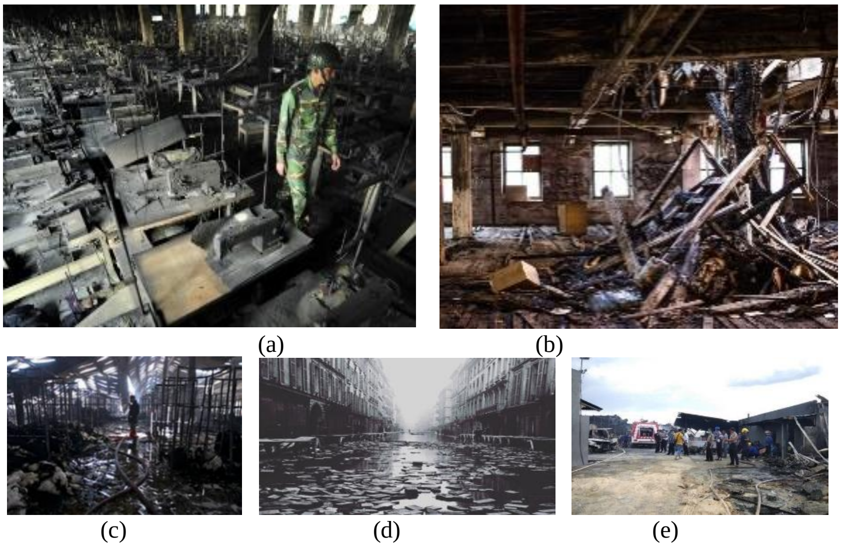


Fig. 6. Wrong Prediction by the proposed system; (Left-Right) (a) After fire damage classified as Damaged Infrastructure; (b) Actual training Damaged Infrastructure image; (c) Fire damage classified as flood damage; (d) and (e) Actual Flood damage training image.

4. Conclusion

Real-time support is the most significant challenge to minimize damages by any disaster; most of the time, the traditional method of assessing the occurrence of disaster and it's characteristics takes too long, and in the meantime, the damage has been done. In this paper, we propose a method to determine the type of disaster automatically from social media images. To test the performance of the proposed idea publicly available dataset collected from [11] is used. Moreover, we extended the dataset by gathering 493 disaster images of six classes from this region, and we are calling it "South Asia disaster" (SAD). Our experiments revealed that the [11] dataset is not diverse and does not perform well recognizing disaster in SAD images. We implemented four different types of deep neural network models: VGG 16, VGG 19, Inception-V3 and Inception-ResNet-V2, for this research. However, to boost up the training speed, we removed the fully connected layer and added a small, fully connected model. To identify the five different disasters: fire disaster, flood disaster, human disaster, infrastructure disaster, and natural disaster; our proposed method with VGG 16 models recognition accuracy is 83.37% on the SAD dataset.

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