National College of Ireland

A Hybrid Model of Sectorization & Evacuation Path Detection for Disaster Affected Areas

MSc Research Project
Data Analytics

Vinaysheel Kishor Wagh
Student ID: x18194303

School of Computing
National College of Ireland

Supervisor:
Dr. Paul Stynes
Dr. Pramod Pathak
Dr. Luis Gustavo Nardin

National College of Ireland

MSc Project Submission Sheet

School of Computing

Student Name:	Vinaysheel Kishor Wagh
Student ID:	X18194303
Programme:	MSc. Data Analytics **Year:** 2019-2020
Module:	Research Project
Supervisor:	Dr. Paul Stynes, Dr. Pramod Pathak, Dr. Luis Gustavo Nardin
Submission Due Date:	17/08/2020
Project Title:	A Hybrid Model of Sectorization & Evacuation Path Detection for Disaster Affected Area
Word Count:	**7992** **Page Count: 19**

I hereby certify that the information contained in this (my submission) is information pertaining to research I conducted for this project. All information other than my own contribution will be fully referenced and listed in the relevant bibliography section at the rear of the project.

ALL internet material must be referenced in the bibliography section. Students are required to use the Referencing Standard specified in the report template. To use other author's written or electronic work is illegal (plagiarism) and may result in disciplinary action.

Signature: Vinaysheel Kishor Wagh

Date: 16/08/2020

PLEASE READ THE FOLLOWING INSTRUCTIONS AND CHECKLIST

Attach a completed copy of this sheet to each project (including multiple copies)	□
Attach a Moodle submission receipt of the online project submission, to each project (including multiple copies).	□
You must ensure that you retain a HARD COPY of the project, both for your own reference and in case a project is lost or mislaid. It is not sufficient to keep a copy on computer.	□

Assignments that are submitted to the Programme Coordinator Office must be placed into the assignment box located outside the office.

Office Use Only	
Signature:	
Date:	
Penalty Applied (if applicable):	

A Hybrid Model of Sectorization & Evacuation Path Detection for Disaster Affected Area

Vinaysheel Kishor Wagh
X18194303

Abstract

Natural disasters' effect such as damage to building-s hit by an earthquake can be detected and classified by monitoring satellite images. The application of image segmentation and classification to the analysis of natural disasters pose several challenges due to complex deep learning techniques and unavailability of data related to disaster prone area. This research proposes a novel method for sectorization and evacuation of natural disaster affected area by integrating image segmentation and classification method with a shortest path algorithm. The proposed method uses a public high-resolution satellite image dataset from Digital Globe. First the buildings are detected from the satellite images using a proposed segmentation model. Then the identified buildings are classified based on their incurred damage severity using a classification model. Finally, the best evacuation path is detected and recommended using the Dijkstra's algorithm. The test set gives an F1-score of 0.84 for the segmentation model and 0.81 for classification model. The evacuation route detection model can generate dynamic evacuation route by analysing real-time satellite images of disaster affected area.

1 Introduction

The unpredictable biological and geophysical processes of earth can cause Natural disasters (Yu, Yang and Li, 2018). These disasters can heavily impact the infrastructure and environment of the affected areas causing loss of shelter, food shortage, spread of infectious diseases and consequently fatalities. In 2019 approximately 11,000 fatalities were reported from 409 natural disasters worldwide and caused countries $100 bn worth in damages, which ranks 2019 as the 11th most costly disaster affected year of the 21st century[1]. An effective monitoring of disaster affected area and immediate post disaster response can reduce fatalities and economic losses. The main challenge of natural disaster management is the monitoring of disaster affected areas. Satellite images provide a macro overview of disaster affected area but the processing of these images and the extraction of required information is a big challenge. Another challenge is the immediate development of exploration strategies such as finding best evacuation route and resource allocation that take into account the hazardous environment condition after a disaster (Bi et al., 2019). An intelligent decision-making system can overcome these challenges by automating the damaged buildings and proposing the shortest and safest path for evacuation.

The proposed research innovates in the field of natural disaster management by proposing a method to sectorize disaster affected areas and a method that can dynamically detect safe evacuation path by analyzing real-time satellite images. The literature in this field are mostly based on big data processing and semantic analysis which depends on real-time data from social media to operate so, it is not reliable and scarce because network connectivity is the

[1] https://www.statista.com/statistics/510959/number-of-natural-disasters-events-globally/

biggest limitation for this type of systems (Ragini, Anand and Bhaskar, 2018). To overcome these challenges the proposed research is focuses on sectorizing the disaster affected area to provide exploration strategies such as the evacuation route taking into account the environment hazardous. Overall, this research helps by providing an overview of the damage cause by the disaster allowing a better prioritization of resources by providing safe evacuation path and sectorization of disaster affected area.

"The aim of this research is to investigate to what extent a hybrid model for sectorization and evacuation can be used to identify disaster affected areas and guide people out of it." To address the research question, following set of research objectives have been identified: -

- Investigate state of the art broadly around post disaster response and risk assessment using deep learning techniques.
- Design a hybrid model for sectorization and exploration of disaster affected area.
- Implement a hybrid model using U-Net, ResNet50 and Dijkstra's algorithm for effectively responding to the post disaster situation.
- Evaluate the hybrid model to measure the prediction accuracy of detecting and classifying damaged buildings from satellite images and dynamic evacuation path detection of the model

The proposed model consists of a sectorization and exploration stages. In sectorization stage buildings are localized in satellite images using segmentation model which is based on the U-NET framework (Pasquali, Iannelli and Dell'Acqua, 2019). Then ResNet50 architecture (He *et al.*, 2015) is used in classification model to classify the disaster affected area based on severity of the damage. Finally, the evacuation path detection model based on Dijkstra's algorithm (Dijkstra, 1959) is used to find the best evacuation path by using the extracted features of previous stage. For model evaluation, the building detection accuracy of the segmentation model is compared with the building extraction model from (Pasquali, Iannelli and Dell'Acqua, 2019). The precision, recall and F1 score of proposed classification model is compared with the VGG network (Simonyan and Zisserman, 2014). And the dynamic behaviour of the evacuation path detection model is also evaluated by analysing dynamic satellite images.

The major contribution of this research is an enhancement of post disaster response which will support rescue teams by sectorizing the disaster affected area and detecting safe evacuation path.

This research focuses only on segmentation and classification of the damaged buildings as the dataset contains annotations of the buildings. Another limitation of this research is that the evacuation path is provided by assuming only one rescue shelter in each disaster affected area.

The remaining paper is organized as follows. Section 2 is literature review of natural disaster management and image processing. Section 3 describes the methodology which explains the research procedure followed in the research. Section 4 demonstrates the implementation details of the proposed model. Section 5 evaluates the performance of the model. Finally, Section 6 concludes the research and discusses the future scope of the proposed research.

2 Related Work

Natural disaster causes huge damage to the society, an automated natural disaster management system can minimize the damage. The existing research in natural disaster management requires further improvement for effectively responding to the post disaster situations (Jung *et al.*, 2020). Three main stages of natural disaster management are analysis, planning and response. There are very few researches focusing on all the three stages together and most of the researches are targeting the analysis and planning phase individually. We require an efficient and complete natural disaster management system comprised of all the three stages to minimize the fatalities and infrastructure loss (Jung *et al.*, 2020). As the proposed research is about sectorization and exploration of disaster affected area, here we briefly describe the existing and relevant researches in the field of natural disaster detection, sectorization of disaster affected area and resource allocation.

This section is categorized as follows: Section 2.1 briefly describes the approaches to post disaster response and recovery. Then Section 2.2 is comprised of segmentation strategies and Section 2.4 demonstrates an overview of exploration strategies. Section 2.4 discusses literature related to Natural disaster management.

2.1 Data Approaches for Post-Disaster Response and Recovery

2.1.1 Big Data and Natural Disasters

Big data has provided innovative solutions for natural disaster management. The huge amount of data provides multiple possibilities for visualization and analysis of the given problem (Yu, Yang and Li, 2018). Natural disasters are unpredictable, thus the analysis of real-time data from disaster areas help in understanding the extent and the effects of the disaster for a more effective and efficient post-disaster response. Satellite images and Unarmed Aerial Vehicles (UAV) also provide huge amounts of data which can be used in disaster mitigation phase (Yu, Yang and Li, 2018). Social media network is widely used for communicating the emergency requests and it gives brief overview of situation of people, so mining the social media content and categorizing them based on severity of affected people can effectively help allocating rescue resources (Ragini, Anand and Bhaskar, 2018). Integrated framework based on Big data, Internet of Things (IoT) and CNN can be used for detecting floods (Anbarasan *et al.*, 2020). IoT generates huge amount of data and big data analytics processes the generated data, then this data is given as input to the CNN model for classifying the chances of occurrence of flood. This framework gave higher accuracy and efficiency because of integration of big data analytics as compare to other deep learning model.

2.1.2 Neural Networks for Disaster Response

Neural network works like human brain and it can extract and describe relationship between given dataset. Synthetic Aperture Radar (SAR) images represent random pattern of dark and light pixels and are useful in detection of oil spill. In (Cantorna *et al.*, 2019) research performance of multiple techniques such as logistic regression, clustering methods and CNN is tested on SAR dataset for detecting marine oil spill. CNN appeared as most suitable solution because of high precision value while classification of oil spill (Cantorna *et al.*, 2019). Satellite images play a vital role in providing in depth knowledge related to the disaster affected areas as they widely capture all the features on the ground surface in a single image and CNN can extract all the required features from the satellite image. The model (Khuzaimah, Amit and Aoki, 2017) efficiently extracted required feature of disaster from satellite images and detected the natural disaster accurately. The results of this model show that deep learning has capabilities to show promising results in natural disaster management. Also, the model is limited for detecting natural disaster whereas by integrating post disaster response system such as resource allocation or finding the evacuation path with this robust feature extraction model could reduce the overall damage caused by the natural disaster.

The main constraint in deep learning is classifying every pixel of the image into particular classes. But (Ronneberger and Fischer, 2015) model can localize and classify every pixel of the given image. The results demonstrate that using this method image segmentation can be performed more precisely with smaller datasets. The U-Net (Pasquali, Iannelli and Dell'Acqua, 2019) model is capable of detecting buildings from satellite images by classifying every pixel of the image. So, this can be integrated in proposed model for segmentation of the images. The ResNet50 (He *et al.*, 2015) model consists of a deep neural network and accurately classifies the given image. The ResNet50 model can be trained using transfer learning technique by changing the output layer. The dense structure of the ResNet50 architecture can precisely and completely classify the given image. So, (He *et al.*, 2015) can be used in classification of disaster affected area.

2.1.3 Data Mining Techniques for Natural Disaster Management

Indonesia is one of the highly affected countries by natural disaster around the globe. It is believed that the tropical climatic conditions of the country are responsible for most of the disasters. In a research by (Prihandoko and Bertalya, 2017)data related to the weather condition and natural disasters of last five year is collected and then this data is analysed using k-means and k-medoid clustering algorithms. It is clearly understood from the result that K-means algorithm is more suitable for analysis of such data as compare to k-medoids and the analysis of k-means algorithm show that intensity of rainfall is responsible for higher number of victims (Prihandoko and Bertalya, 2017). Wildfires are most unpredictable and devastating natural disaster which causes huge financial and life loss. The availability of satellite images has contributed in research related to natural disaster management. And using the satellite images (Sayad, Mousannif and Al Moatassime, 2019) author has developed an integrated framework based on Big data, Artificial neural network (ANN) and SVM to predict the occurrence of wildfires. In this framework ANN gave an accuracy of 98% whereas SVM gave 97% accuracy (Sayad, Mousannif and Al Moatassime, 2019). The disadvantage of integrating ANN is, the complex structure of this neural network creates computationally complex system.

In (Chen and Li, 2020) research, data fusion technique fuzzy inference is used for knowledge extraction, then model is trained using SVM based on given dataset. There is wide variety of data such as social media content, satellite images and geographical data related to natural disaster is available and this can give in-depth knowledge related to the disaster. So, the data fusion techniques are beneficial for gathering more information and it can help in building accurate model. Landslide is also one of devastating natural disaster which causes fatalities and infrastructure loss. The conventional machine learning algorithms i.e. support vector machine (SVM), random forest (RF) and logistic regression are powerful in landslide susceptibility mapping (Fang *et al.*, 2020) and CNN can accurately extracts required feature from the images. So, (Fang *et al.*, 2020) proposed a hybrid model based on conventional machine learning and CNN technique. The results of this model demonstrated that the integration of CNN with conventional algorithm enhances the performance of the landslide susceptibility mapping by effectively extracting required (Fang *et al.*, 2020).

2.2 Segmentation Strategies

The monitoring of disaster affected area can improve the efficiency of post disaster response. The classification of disaster affected area into different categories based on intensity of damage is sectorization. In (Peng *et al.*, 2012) research, local binary pattern (LBP) is used with fuzzy clustering method for image segmentation. LBP extracts required feature more precisely and reduces the noise from the image. The results of (Peng *et al.*, 2012) this research demonstrated that integration of LBP with fuzzy clustering method improves the accuracy of Image segmentation by overcoming the problem of initial cluster sensitivity. (Saraswathi and Allirani, 2013) reviews research in field of image segmentation based on clustering. (Saraswathi and Allirani, 2013) has analyzed and explained hierarchical clustering, partitional clustering, k-means clustering and fuzzy clustering methods in this paper. The effectiveness of the research is enhanced by implementing all the clustering method on a dataset and by comparative analysis of their results.

Earthquakes are devastating natural disaster that results in fatalities and damages, but a quick and efficient post disaster response such as damage building detection and rescue could reduce the fatalities. Khodaverdizahraee, Rastiveis and Jouybari proposes a novel method for detecting damaged building by segment wise comparing of pre disaster and post disaster images. The model initially extracts required feature from pre & post disaster images and their differences then this feature vector is given as input to the classification model. The model resulted into 92% accuracy while generating damage building map (Khodaverdizahraee, Rastiveis and Jouybari, 2020). This model evaluates every image by performing comparison of pre and post disaster image which is a time-consuming process and can result in a feature loss. So, the pre & post disaster image comparison can be enhanced by adding feature extraction technique such as CNN to improve the performance of satellite image classification.

2.3 Resource Allocation Strategies

Post disaster response is the main part of disaster recovery planning and it can effectively reduce the economical and life loss caused by the natural disaster. The change detection technique measures the difference between pre and post disaster multi temporal satellite images and then the difference image is divided into multiple clusters (Soleh, Arymurthy and Wiguna, 2018). Fuzzy C means clustering and k means clustering methods were used in the research. The overall research (Soleh, Arymurthy and Wiguna, 2018) is limited to disaster affected area detection and author did not mention any method for disaster recovery planning. Post disaster rescue operation requires a coordination between rescue team and it has been observed that the lack of coordination reduces the efficiency of rescue operations. Mondal *et al.(* 2019) developed an efficient resource allocation problem (RAP) for allocation of food, clothes, medical help and rescue team. Particle swarm optimization (PSO), genetic algorithm and differential evolution method was used in the research and among these techniques PSO allocated resources more accurately. The findings of this research represent that PSO can reduce the loss caused by natural disaster by accurately providing available resources so, this can be considered as a best solution to the resource allocation problem (Mondal *et al.*, 2019).

But the effectiveness of the research could be enhanced by finding the best evacuation path which could improve the overall performance of the system.

The analysis of disaster risk assessment helps in disaster recovery planning and disaster prevention. Chen *et al.* (2019) have provided a multi criteria decision model to evaluate risk of disaster in China. The model consists of self-organizing map, clustering, visualizing and ranking techniques. The findings of the research provide a way to plan emergency operation and also provides suggestions in decision making to prevent and mitigate the natural disaster. Computational complexity and dependency on data from multiple sources is the main limitation of the model (Chen *et al.*, 2019). Evacuation route is necessary for the refugees trapped in disaster and also for the rescue team for evacuation of people affected by natural disaster. The hybrid model consist of auto encoder method and reinforcement learning is proposed by the author to find global optimum evacuation route (Bi *et al.*, 2019). The auto encoder technique reduces the data and then Markov Decision Process (MDP) predicts the best evacuation route based on provided state, action and reward. The efficiency of the model with metrological data of Japan demonstrates the usefulness of the model (Bi *et al.*, 2019).

2.4 Natural Disaster Management using Satellite Imagery

The monitoring of natural disaster affected areas is difficult due to their physical extent and geography. Satellite images can be used for monitoring of disaster affected areas. The Computer Vision, Semantic Segmentation techniques are widely used for extracting the features from satellite images Doshi, Basu and Pang (2018) propose the change-detection framework to find severely natural disaster affected areas using satellite images. The CNN is used to detect buildings and roads from the input image and then prediction mask is formed to detect damaged area. This method resulted into F1 score of 83.5%. The segmentation of disaster affected areas using their model has the capability to extract different features such as buildings, road, waterways, trees and empty spaces from the satellite images (Doshi, Basu and Pang, 2018). This can be followed in the proposed natural disaster sectorization approach to extract buildings from the satellite images.

Community resilience is a major factor in post disaster recovery of disaster affected area. Night Time Light (NTL) images can be used as data for measuring community resilience on earth surface after a natural disaster (Qiang, Huang and Xu, 2020). They use time series to measure the resilience by monitoring the disaster affected area using NTL images. The result of the model demonstrated the diversity of resilience in different communities and their improvement after each disaster recovery phase. It mainly analyses the recovery pattern of the economy and does not deal with immediate post disaster response (Qiang, Huang and Xu, 2020). The post disaster decision support requires an intelligent decision-making system and detailed data related to the disaster affected area for immediate and accurate post disaster response planning. (Chaudhuri and Bose, 2020) tackle this issue by extracting required complex information from images of disaster affected area. The main benefit of applying deep learning technique is it gives high efficiency and while responding to the post disaster situation higher efficiency is mandatory for immediate allocation of resources to the disaster affected area (Chaudhuri and Bose, 2020).

2.5 Discussion

In conclusion, the monitoring of the disaster affected area can improve the post disaster response and satellite images can capture all the elements of ground surface (Doshi, Basu and Pang, 2018). So, satellite images can help in effective area monitoring. The sectorize disaster affected area helps in resource allocation and CNN works as best image feature extractor. Thus, CNN based techniques can be followed in the research for disaster affected area sectorization. The extracted feature can be analysed to find the evacuation path for the refugees (Bi *et al.*, 2019). The safe and short evacuation path can be detected by using (Dijkstra, 1959)algorithm. In this way the proposed research can used deep learning technique and shortest path algorithm for sectorization and evacuation path detection of disaster affected area.

3 Methodology

The Knowledge Driven Discovery (KDD) (Lambert and Fahlman, 2007) approach is followed in the research and this section describes the research methodology used in the research.

3.1 Data Selection & Understanding

The satellite image dataset of natural disaster affected area is collected from the xBD Dataset repository[2] (Gupta *et al.*, 2019). Then the data is categorized into multiple folders according to the name of disaster. The dataset covers 5000km^2 of disaster affected area and it contains 7500 pre disaster and post disaster satellite images. The dataset contains satellite images of different type of disasters such as hurricane, volcano, floods, earthquake, tsunami and wild fires. All images are annotated and the annotation file contains building polygon co-ordinate, classification of disaster affected area with intensity of damage and also contains satellite metadata. The buildings from a satellite image is annotated as polygons using ISO/IEC 13249-3:2016 standard ('ISO/IEC 13249-3', 2016). Table 1 contains the joint damage scale used in the dataset for classification of disaster affected area. Figure 1 and 2 represent the pre and post disaster image of Mexico earthquake which damaged Puebla, Morelos and Greater Mexico City area in 2017.

Table 1: Joint Damage Scale

Disaster Level	Structure Description
0 (No Damage)	Undisturbed. No sign of water, structural or shingle damage, or burn marks.
1 (Minor Damage)	Building partially burnt, water surrounding structure, volcanic flow nearby, roof elements missing, or visible cracks.
2 (Major Damage)	Partial wall or roof collapse, encroaching volcanic flow, or surrounded by water/mud.
3 (Destroyed)	Scorched, completely collapsed, partially/completely covered with water/mud, or otherwise no longer present

[2] https://xview2.org/download

Figure 1: Pre-Disaster of Puebla

Figure 2: Post-Disaster of Puebla

3.2 Data Pre-processing and Transformation

At first, the dataset is divided into train and test set using 80:20 split ration with random data shuffling. The dataset contains images from multiple disasters, so for better understanding and analysis of particular disaster affected area, the dataset directory is divided into multiple subdirectories according to the name of particular disaster. Then mean pixel value of the training data directory is computed by calculating global mean of all three-color channels of the given image. The dataset is centered by subtracting the mean pixel value from the pixel values of training set. Then the images are converted into arrays and the dataset is normalized by dividing each pixel value by 255 which generates pixel in range of 0-1. To enhance the performance of the model, size of the dataset is increased by using horizontal flip, vertical flip and random crop data augmentation techniques. Then the processed and transform data is given as input to the segmentation and classification model.

For evacuation route detection model, the data such as building polygon co-ordinates, latitude, longitude, intensity of disaster and satellite data from the label files of each training image is loaded into a data-frame. The mean of the latitude and longitude is computed to get the map of that area. The damage type is parsed from the dataset and a dictionary of damage type as key and color code as value is defined for the purpose of visualization. Then this data-frame is given as input to the evacuation path detection model.

3.3 Data Mining

The proposed hybrid model is consisting of a segmentation model and a classification model. The post disaster response can be enhanced by sectorizing disaster affected areas and by detecting evacuation path. For detecting the disaster affected buildings from the satellite images, segmentation model is proposed in the research. The segmentation model consists of a U-Net architecture (Pasquali, Iannelli and Dell'Acqua, 2019). This model mainly extracts the buildings from the satellite images by classifying each pixel into two classes: building and background. The model also generates polygon co-ordinates of each detected building from the satellite image, so the predicted value of the co-ordinate is compared with the actual value from the annotated label file to measure the accuracy of the model by calculating the intersection over union (IOU) (Caicedo *et al.*, 2019).

To sectorize the disaster affected area into no-damage, minor-damage, major-damage and destroyed classes, the segmented images generated by the proposed segmentation model is given as the input to the classification model. The classification model categorizes the disaster affected building into one of the four categories. The proposed classification model is based on ResNet50 architecture (He *et al.,* 2015). The combination of segmentation model and classification model can extract all the buildings from the satellite images and the dense neural network structure accurately classifies all the extracted buildings. Also, another benefit of this combined model is it becomes easy for classification model to classify the images by processing the extracted features of segmentation model.

Finally, to detect the evacuation path from a disaster affected area to the rescue shelter, an evacuation path detection model is proposed in the research. This model takes the features extracted by the segmentation and classification model as input and generates an evacuation path based on Dijkstra's algorithm (Dijkstra, 1959). The output of the segmentation and classification model provides in-detail overview of the disaster affected area which helps the evacuation path detection model in generating accurate and safe path. Thus, all of the proposed models extract the required useful information from the satellite images and accordingly sectorizes disaster affected area and generates the safest and shortest evacuation path. Section 4 provides further details related to design of the proposed hybrid model.

3.4 Model Evaluation

The segmentation model is evaluated by measuring the IOU and F1-score value for the test dataset. The IOU determines how accurately model is classifying every pixel of the image to detect buildings from the satellite images. And F1-score represents the balance between the precision and recall of the model. The IOU of the model is again evaluated by performing a hypothesis test on the IOU value of segmentation model and building extraction model (Pasquali, Iannelli and Dell'Acqua, 2019). The classification model is evaluated using general performance metrics such as precision, recall and F1-score (Caicedo *et al.,* 2019). Precision is how exactly model is classifying the given image and recall describes the model's capacity to completely classify all the given images. Section 6 describes in detail evaluation of the proposed model using above mentioned performance evaluation metrics.

4 Design Specification

Figure 3 illustrates the design specification of the proposed hybrid model. The model consists of three parts. The first part is a segmentation model which performs image segmentation and extracts the buildings from the satellite images. For this satellite images are processed and transform using image centering, data normalization and augmentation techniques. In data centering mean pixel value of the dataset is computed and subtracted from the pixel values. Then these centered images are normalized to the value in range of 0-1 and random flip and crop of image is performed in data augmentation phase. Then U-Net model classifies every pixel of the image and detects buildings from it. The segmented image is given as input to the classification model.

Then in second part classification model classifies segmented post-disaster image into no damage, minor damage, major-damage and destroyed categories using ResNet50 architecture. The random data transformation creates multiple images of the input image by performing vertical flip, horizontal flip and image rescaling. The ResNet50 architecture is implemented using transfer learning technique by integrating pre-trained convolution base with 3-convolution layer followed by ReLU activation function and max pooling layer. Then the dense structure of the classification model performs effective disaster affected area sectorization.

In third part, a data-frame is generated from the extracted features of classification model. This data-frame is processed to visualize disaster affected area on the map. Then an evacuation route is detected between a particular highly damaged area and rescue shelter using Dijkstra's algorithm. The model always checks if next co-ordinate lies in disaster affected area, if yes then backpropagates to the previous point and if two destination co-ordinates are available then the one with less distance is selected by the model. In this way, model can analyze sectorize disaster affected area and detect safe and short evacuation route.

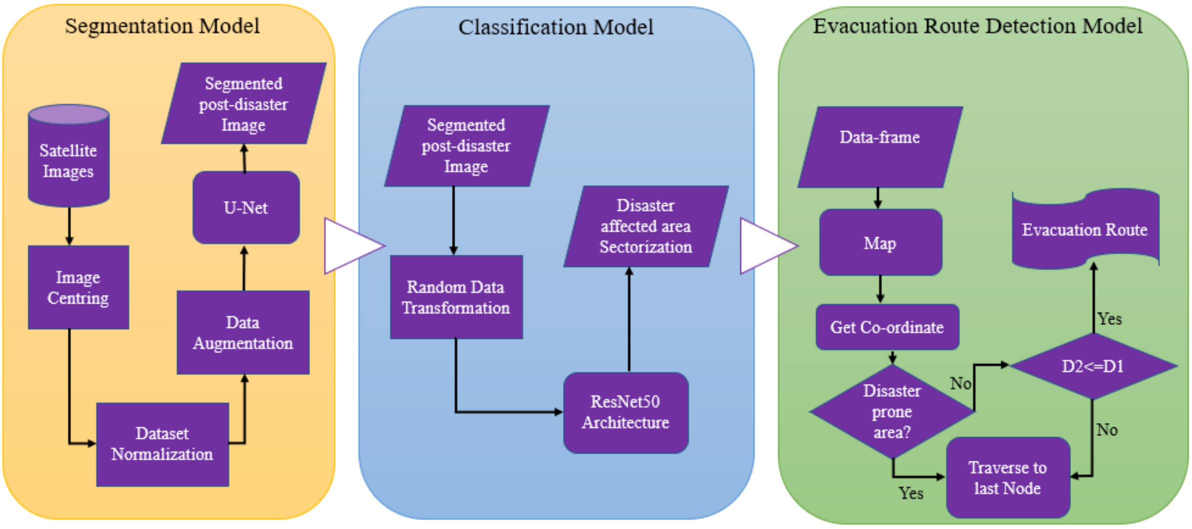

Figure 3: Design Specification

5 Implementation

This section describes the implementation of the proposed model. The implementation of the proposed framework is divided into segmentation model, classification model and evacuation path detection model. So, each model is separately discussed in the following subsections.

5.1 Segmentation Model

First the segmentation model is implemented for detecting buildings from the satellite images. The segmentation model consists of U-Net architecture. The U-Net architecture is based on CNN and it can localize the buildings from the image because this architecture classifies every pixel from the input image. Figure 4 illustrates the U-Net architecture. The left-side of the architecture is contraction path and right side is expansive path. The contracting path is implemented using multiple 3×3 convolutions followed by rectified linear unit (ReLU) activation function. At every step of contraction, down sampling is performed and the feature channel is doubled using the 2×2 max pooling layer. The expansive path performs up sampling and halves the number of feature channel using 2×2 convolutions at every step. This path also contains concatenation of feature map from contraction path and two 3×3 convolutions followed by ReLU at each step. Finally, 1×1 convolution is used for output feature mapping.

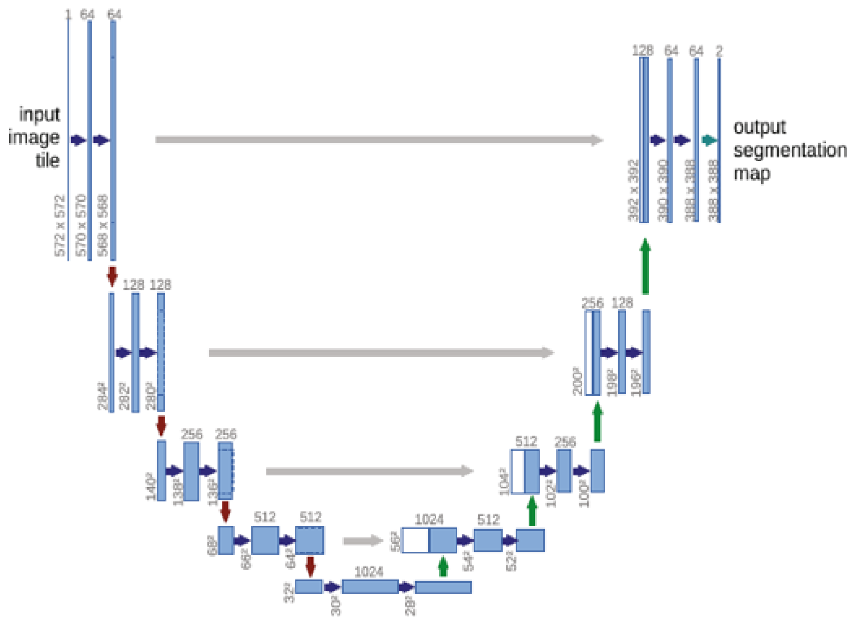

Figure 4: U-Net Architecture

The model is implemented using Adam optimizer by keeping the learning rate at 0.0001 and by setting the number of epochs equal to 100. This model is developed in Python 3.7 by using the Tensorflow-GPU, Keras, NumPy and chainer library. The segmentation model is giving an accuracy of 81.31% and intersection over union (IOU) is 0.73. The following figure shows an example of input and output of the segmentation model. In output image white polygons represents buildings and remaining everything from the satellite image is classified as black pixels. In this way proposed segmentation model is detecting buildings from the satellite images.

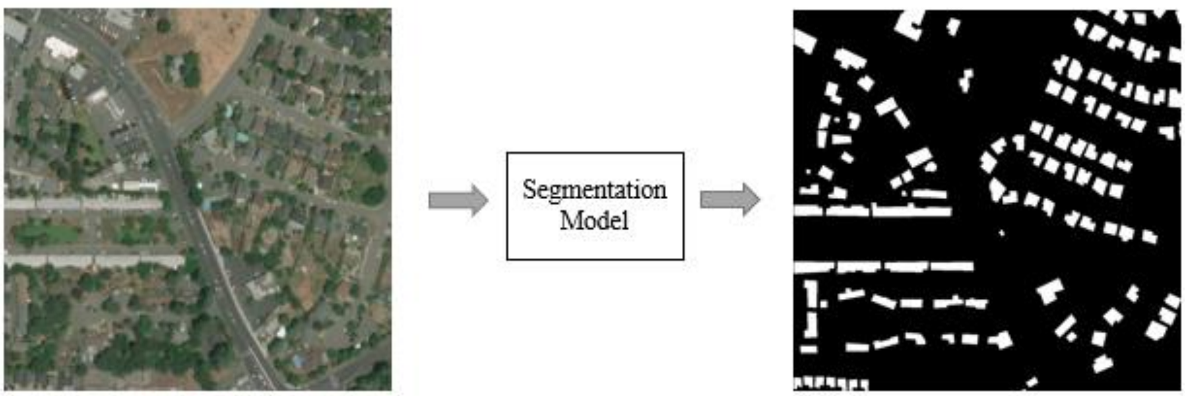

Figure 5: Segmentation Model

5.2 Classification Model

To sectorize the disaster affected buildings into no-damage, minor-damage, major-damage and destroyed categories classification model is implemented in the proposed research. The classification model consists of ResNet50 architecture which is based on CNN. The classification model is implemented using the transfer learning technique in Python. Thus, pretrained ResNet50 model of Keras library is used as the convolution base and it is concatenated with another 3-convolution layer followed by the relu activation function and max-pooling layer. The model is trained by keeping batch size = 64, learning rate = 0.0001 and number of epochs to 50. Figure 6 illustrates the output of the proposed classification model. The output image of the classification model contains polygons with red, blue and green color, where green polygons represents safe buildings and red represents destroyed buildings.

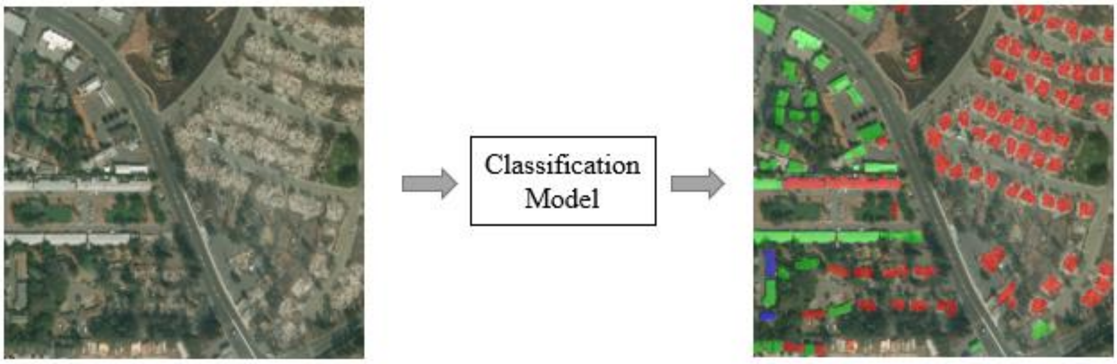

Figure 6: Classification Model

5.3 Evacuation Path Detection Model

After sectorization of disaster affected buildings evacuation path detection model is implemented using numpy, pandas, shapely, matplotlib and folium libraries of Python 3.7 to detect evacuation path from the disaster affected area. The proposed evacuation route detection model is based on Dijkstra's algorithm. First the label data from JSON file of each post disaster satellite image is loaded into a Pandas data-frame. Each row of the data-frame represents each satellite image from the dataset and it contains centroid of the image, latitude, longitude, type and count of damaged buildings.

To get the map of the disaster affected area, mean of centroid column is computed and the resulted x, y co-ordinate is given as input to the folium.map() method. Then the disaster affected areas are plotted on the map in form of circle, where the diameter of the circle represents the area covered by the disaster and color of the circle shows the intensity of the disaster. The value of centroid is taken as center and the damage intensity is considered as the radius of the circle.

The rescue shelter is assumed as the hospital in the 5km radius of the disaster affected area and the co-ordinates of the hospital is generated by the googlemaps library. Then an evacuation route between particular disaster affected location and a rescue shelter is detected using the Dijkstra's algorithm. First the co-ordinates of each point and available routes from source to the destination is generated using googlemaps library. Then for each co-ordinate isInside() function checks whether it lies in the highly damaged or destroyed area, if the co-ordinate lies in destroyed or highly damaged area getSafeCoord() function backpropagates to the previous co-ordinate and generate alternative route from that co-ordinate to the rescue shelter. In this way iteratively Dijkstra's algorithm produces safe evacuation route. Figure 7 shows a visualization of disaster affected area and output of the evacuation route detection model.

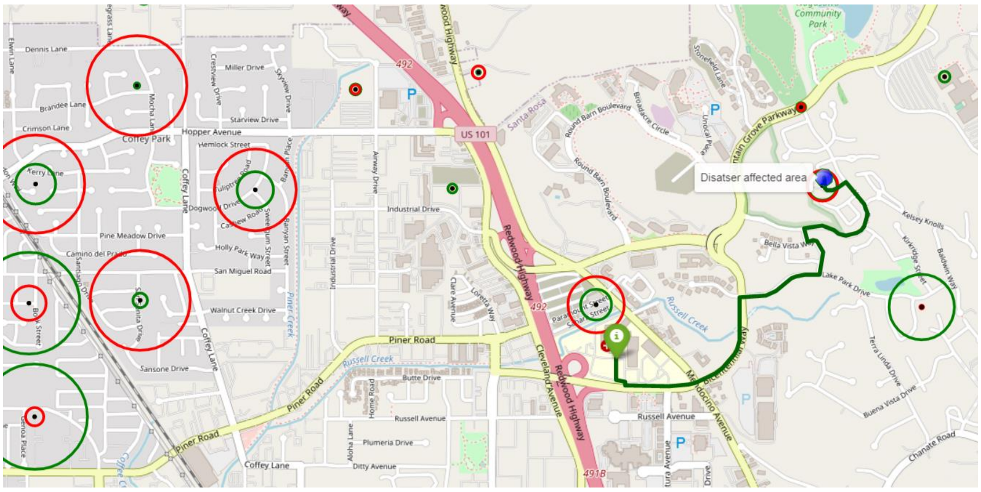

Figure 7: Evacuation Path Detection Model

6 Evaluation

This section evaluates the proposed models. The result of segmentation model is compared with building extraction model (Pasquali, Iannelli and Dell'Acqua, 2019) in experiment 1. In experiment 2 the performance of the classification model is compared with vgg16 and vgg19 model (Simonyan and Zisserman, 2014) using general evaluation metrics like precision, recall and F1 score. Then experiment 3 evaluates dynamic behavior of the evacuation path recommendation system by analyzing newly gathered satellite data.

6.1 Experiment 1: Evaluation of Segmentation Model

The proposed segmentation model is compared with the building footprint extraction model proposed in (Pasquali, Iannelli and Dell'Acqua, 2019). The comparison is performed using the F1 score and intersection over union (IOU). Both models are based on U-Net architecture and are evaluated using the xBD dataset (Gupta *et al.*, 2019). The test data consist of 1866 annotated satellite images.

For comparison purposes, the building footprint extraction model is initially trained using the settings reported in (Pasquali, Iannelli and Dell'Acqua, 2019). Then the proposed segmentation model parameters are tuned to enhance the segmentation model's performance. Table 2 contains the value of the parameters used in this experiment for both the models.

Table 2: Parameters of U-Net model

Parameter\Model	Building Footprint Extraction	Proposed Segmentation Model
Epoch	100	100
Learning Rate	0.001	0.0001
Mini-Batch Size	16	4
Batch Normalization	No	Yes
1024 Depth Layer	No	Yes

The results are shown in Table 3. The results show that the proposed segmentation model is more accurate in distinguishing between the background and the building classes as the IOU of the proposed segmentation model is greater than 0.7. Also, the F1 score is greater than the building extraction model which means that the proposed segmentation model generates less false negatives and less false positives compared to the building extraction model.

Table 3: Results of U-Net Model

Model	F1 Score	IOU
Building footprint extraction	0.79	0.68
Proposed segmentation model	0.84	0.73

The performance of the proposed model is further analyzed by performing hypothesis test on the IOU values of both the models. Thus, can we say that the IOU of proposed segmentation model has a statistical difference than the results from building extraction model? Here, the statistical significance of this difference is evaluated using Wilcoxon rank sum test (Haynes, 2013). For this test, the null hypothesis states that the IOU of segmentation model and building extraction model is similar to each other and the alternate hypothesis is that the IOU of segmentation model is greater than the building extraction model. The p-value of the hypothesis test is 0.003383 and true location shift is greater than 0.022. As the p-value is smaller than 0.05 thus, the null hypothesis is rejected and the alternate hypothesis can be accepted at 0.05 significance level. This means that the IOU value of segmentation model is greater than the building extraction model at 0.05 significance level. The results of this experiment clearly state that proposed model performs better than the building footprint extraction model after tuning the performance of the U-Net.

6.2 Experiment 2: Evaluation of the Classification Model

The disaster affected area is classified using the ResNet50 architecture which is based on CNN. In this section the proposed classification model using ResNet50 architecture (He *et al.*, 2015) is evaluated against VGG16 and VGG19 architectures (Simonyan and Zisserman, 2014). For this experiment the VGG16 and VGG19 models are trained using the transfer learning technique. First, pretrained weights of VGG16 and VGG19 architectures is used as convolution base and then max-pooling layer followed by relu activation function is integrated in the network to classify damaged buildings.

The model is evaluated using the same test data from experiment 1 which consist of 1866 annotated satellite images from xBD dataset (Gupta *et al.*, 2019). For applying the classification models on the test dataset, all of the satellite images are pre-processed to extract buildings polygon image from it. A total 54862 building images of different categories such as ‘no-damage’, ‘minor-damage’, ‘major-damage’ and ‘destroyed’ are created, then these images are given as input to the VGG16, VGG19 and ResNet50 architecture. All the models are trained using the hyper parameters from Table 4.

Table 4: Parameters Value

Parameters	Value
Epoch	50
Learning Rate	0.0001
Batch Size	64

Workers	4
Activation	Relu

Finally, the proposed classification model is evaluated by comparing its precision, recall and F1 score with VGG16 and VGG19 model. Table 5 shows the performance of the ResNet50, VGG16 and VGG19 models.

Table 5: Evaluation of Classification Model

Model	Precision	Recall	F1-Score
VGG16	0.82	0.67	0.71
VGG19	0.80	0.69	0.73
Classification Model (ResNet50)	0.83	0.74	0.81

The results show that the proposed classification model based on ResNet50 architecture is performing better than other classification model based on VGG16 and VGG19 architecture. The precision and recall of ResNet50 is more balanced than the VGG16 and VGG19 because the ResNet50 architecture are denser and can perform correct and complete classification. And, F1 score is also greater than VGG network which gives less false negatives in case of ResNet50 architecture.

6.3 Experiment 3: Evaluation of Dynamic Evacuation Path

The evacuation route is recommended by the proposed system after sectorizing the disaster affected buildings. The dynamic behavior of the evacuation path recommendation system is evaluated by analyzing real-time satellite images. This experiment is performed by assuming a hospital within 5km radius as rescue shelter. The JSON label files from the test dataset is grouped according to the disaster and a particular disaster is selected from it for finding evacuation route. Then a data-frame is generated by extracting required features from the JSON files of the test dataset. In the data-frame every row represents a different satellite image and the columns are consist of details related to damage type with intensity of the damage, image name, id, centroid of the image and sensor details. The disaster affected area is marked using circles of multiple colors where red represent high damage and green is for no-damage. The radius of the circle represents the approximate area covered by the damaged or undamaged buildings.

The googlemaps library is used to find nearby hospital within 5km radius of particular disaster affected area. The direction between the disaster affected area and a hospital which is rescue shelter is generated by using Dijkstra’s algorithm. Figure 8 shows the output of the evacuation path model (dark green line).

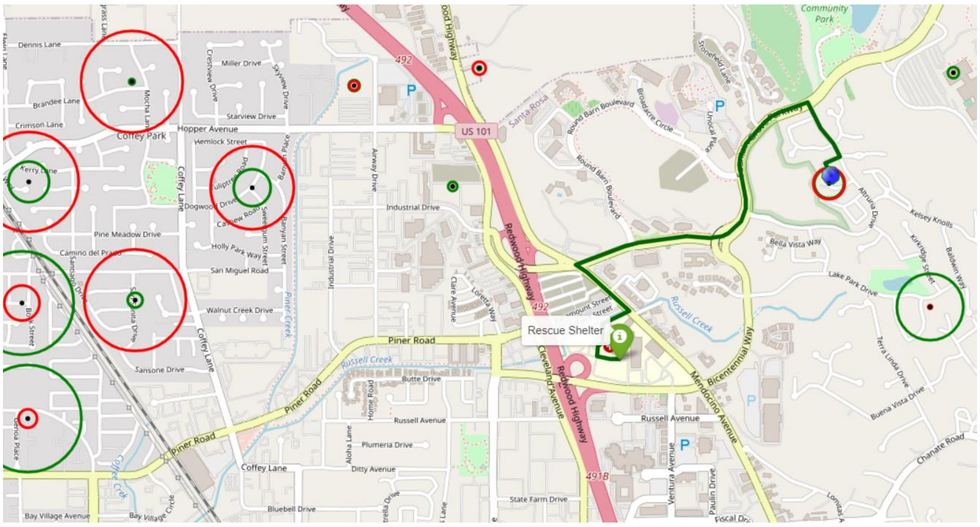

Figure 8: Evacuation route before updating data

To measure the dynamic capability of the proposed evacuation path model, new data related to the disaster is used to update data-frame and again the evacuation path is generated using the proposed model. Figure 9 shows newly generated output of the proposed evacuation path model (dark green line).

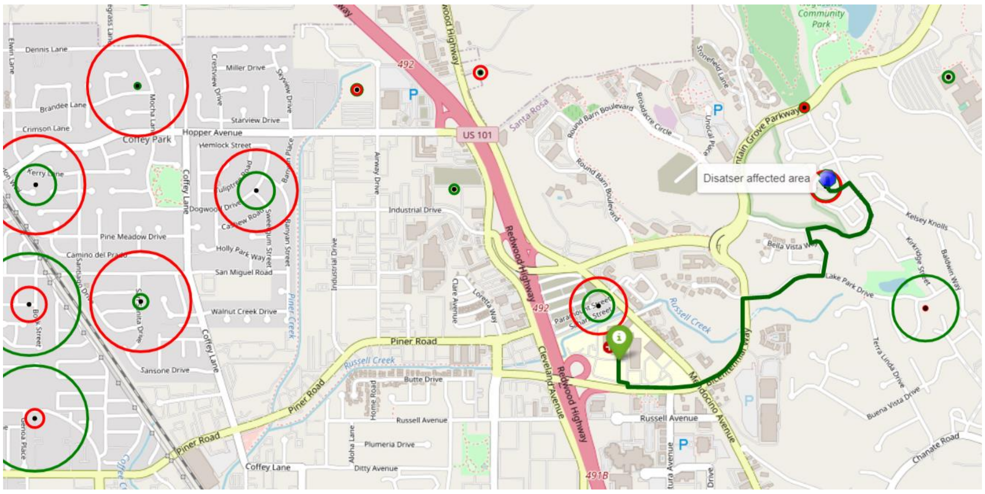

Figure 9: Evacuation route after updating data

The outputs in Figure 8 and Figure 9 illustrates that the proposed evacuation path model can dynamically adjust the shortest and safest evacuation path proposed using real-time satellite images.

6.4 Discussion

The comparison of the proposed segmentation model and building extraction model shows that the proposed model is capable of effectively segmenting the buildings from the satellite images using U-Net architecture. The IOU value is 0.73 which represents that overall, 73% of the pixels from test dataset are correctly segmented as buildings. In some cases, the model is predicting multiple building as one building because multiple buildings are closely connected to each other. The F1 score is 0.84 which is also greater than the F1 score of building footprint extraction model. Also, the result of the Wilcoxon rank sum test indicates that the proposed model is more accurate in segmenting the buildings from satellite images. The p-value of the hypothesis test is smaller than 0.05 which allows acceptance of the alternate hypothesis that states that the IOU of segmentation model is greater than the building extraction model. The results of the U-Net model comparison represents that the proposed model is performing better as compare to the building footprint extraction model (Pasquali, Iannelli and Dell'Acqua, 2019).

For sectorization, the disaster affected area is classified into no-damage, minor-damage, major-damage and destroyed categories. This classification is performed using the ResNet50 architecture. The proposed classification model based on ResNet50 architecture has precision equal to 0.83 and recall equal to 0.74 that means there are few false positives and false negatives predicted by the model. This suggests that the dense structure of the neural network is capable of classifying the buildings from the satellite images. The natural disaster management system requires efficient model for immediate response to post disaster scenarios and the proposed classification model is suitable for such scenarios as it has F1 score of 0.81, which means that the model can classify disaster affected areas with a high accuracy.

The next stage of proposed hybrid model is to recommend the evacuation path taken into account the hazardous environment. The output of the proposed segmentation and classification model is given as input to the evacuation path recommendation model in form of data-frame. The proposed evacuation path model is capable of detecting the shortest and safest evacuation route. Natural disasters are unpredictable, so the disaster situation can change after some time. In such scenarios the proposed model can dynamically adjust the evacuation path recommended by analyzing the previous data and newly generated satellite data.

Overall, the proposed hybrid model is capable of detecting buildings from the satellite images and can also effectively sectorize the disaster affected area. The integration of evacuation path detection model enhances the capabilities of the model by detecting evacuation path based on analysis of sectorized disaster affected area.

7 Conclusion and Future Work

The proposed model shows promising results for disaster affected area sectorization and evacuation path detection. Thus, the research question is answered as the proposed hybrid model can guide anyone out of the disaster affected area and can also help rescue teams in arranging the rescue operations. The hybrid model is implemented using a combination of U-Net, ResNet50 and Dijkstra's algorithm. The segmentation model and classification model accurately detect and classifies damaged buildings. Also, the evacuation path detection model generates dynamic evacuation paths. Overall, the investigation, design, implementation and evaluation of the proposed hybrid model is performed in the research which fulfils all the research objectives. In heavily damaged areas the model can-not determine safe evacuation route as the dataset do not contain any information related to the condition of the road.

The proposed research can be further extended by training the proposed model on a satellite image dataset which contains information of damaged buildings as well as road conditions of that area. As part of future work, resource allocation can be implemented on top of proposed work which can allocate resources based on sectorize disaster affected area and can plan rescue operations based on the safety and distance of the evacuation route.

Acknowledgement

I am immensely grateful to my supervisors Dr. Paul Stynes, Dr. Pramod Pathak and Dr. Luis Gustavo Nardin for their constant valuable guidance and motivation throughout this semester. I would also like to thank my friends and family for always trusting and believing in me.

References

Anbarasan, M. *et al.* (2020) 'Detection of flood disaster system based on IoT, big data and convolutional deep neural network', *Computer Communications*, 150, pp. 150–157. doi: 10.1016/j.comcom.2019.11.022.

Bi, C. *et al.* (2019) 'Evacuation route recommendation using auto-encoder and Markov decision process', *Applied Soft Computing Journal*, 84. doi: 10.1016/j.asoc.2019.105741.

Caicedo, J. C. *et al.* (2019) 'Evaluation of Deep Learning Strategies for Nucleus Segmentation in Fluorescence Images', *Cytometry Part A*. Wiley-Liss Inc., 95(9), pp. 952–965. doi: 10.1002/cyto.a.23863.

Cantorna, D. *et al.* (2019) 'Oil spill segmentation in SAR images using convolutional neural networks. A comparative analysis with clustering and logistic regression algorithms.', *Applied Soft Computing Journal*, 84. doi: 10.1016/j.asoc.2019.105716.

Chaudhuri, N. and Bose, I. (2020) 'Exploring the role of deep neural networks for post-disaster decision support', *Decision Support Systems*, 130. doi: 10.1016/j.dss.2019.113234.

Chen, G. and Li, S. (2020) 'Research on location fusion of spatial geological disaster based on fuzzy SVM', *Computer Communications*, 153, pp. 538–554. doi: 10.1016/j.comcom.2020.02.033.

Chen, N. *et al.* (2019) 'Regional disaster risk assessment of china based on self-organizing map: Clustering, visualization and ranking', *International Journal of Disaster Risk Reduction*, 33, pp. 196–206. doi: 10.1016/j.ijdrr.2018.10.005.

DIJKSTRA, E. W. (1959) 'A Note on Two Problems in Connexion with Graphs', *Numerische Mathematlk*, pp. 269–271. doi: 10.1007/978-3-540-77978-0.

Doshi, J., Basu, S. and Pang, G. (2018) 'From Satellite Imagery to Disaster Insights', in *Conference on Neural Information Processing Systems*. Montreal, Canada. Available at: http://arxiv.org/abs/1812.07033 (Accessed: 18 March 2020).

Fang, Z. *et al.* (2020) 'Integration of convolutional neural network and conventional machine learning classifiers for landslide susceptibility mapping', *Computers and Geosciences*, 139. doi: 10.1016/j.cageo.2020.104470.

Gupta, R. *et al.* (2019) 'xBD: A Dataset for Assessing Building Damage from Satellite Imagery', in *CVPR 2019*. Computer Vision Conference, pp. 10–17. Available at: http://arxiv.org/abs/1911.09296.

Haynes, W. (2013) 'Wilcoxon Rank Sum Test', in *Encyclopedia of Systems Biology*. doi: 10.1007/978-1-4419-9863-7_1185.

He, K. *et al.* (2015) 'Deep Residual Learning for Image Recognition'. Available at: http://arxiv.org/abs/1512.03385 (Accessed: 27 July 2020).

'ISO/IEC 13249-3' (2016). Jeneva, CH: Information technology — Database languages — SQL multimedia and application packages — Part 3: Spatial. Standard, International Organization for Standardization.

Khodaverdizahraee, N., Rastiveis, H. and Jouybari, A. (2020) ‘Segment-by-segment comparison technique for earthquake-induced building damage map generation using satellite imagery’, *International Journal of Disaster Risk Reduction*, 46. doi: 10.1016/j.ijdrr.2020.101505.

Khuzaimah, S. N., Amit, B. and Aoki, Y. (2017) ‘Disaster Detection from Aerial Imagery with Convolutional Neural Network’, in *2017 International Electronics Symposium on Knowledge Creation and Intelligent Computing (IES-KCIC)*. Surabaya, Indonesia.

Lambert, B. and Fahlman, S. E. (2007) ‘Knowledge-driven learning and discovery’, *Proceedings of the National Conference on Artificial Intelligence*, 2(Fahlman 2006), pp. 1880–1881.

Mondal, T. *et al.* (2019) ‘Distribution of deficient resources in disaster response situation using particle swarm optimization’, *International Journal of Disaster Risk Reduction*, 41. doi: 10.1016/j.ijdrr.2019.101308.

Olaf Ronneberger, Philipp Fischer, T. B. (2015) ‘U-Net: Convolutional Networks for Biomedical Image Segmentation’, in *18th International Conference on Medical Image Computing and Computer-Assisted Intervention, MICCAI 2015*. Munich; Germany: Springer Verlag, pp. 234–241.

Pasquali, G., Iannelli, G. C. and Dell’Acqua, F. (2019) ‘Building footprint extraction from multispectral, spaceborne earth observation datasets using a structurally optimized U-Net convolutional neural network’, *Remote Sensing*, 11(23), pp. 1–21. doi: 10.3390/rs11232803.

Peng, L. *et al.* (2012) ‘Application of improved fuzzy clustering method in the image segmentation’, in *Proceedings - 2012 5th International Symposium on Computational Intelligence and Design, ISCID 2012*, pp. 61–64. doi: 10.1109/ISCID.2012.167.

Prihandoko, Bertalya, M. I. R. (2017) ‘An Analysis of Natural Disaster Data by Using K-Means and K-Medoids Algorithm of Data Mining Techniques’, in *International Symposium on Electrical and Computer Engineering Quality in Research*, pp. 221–225.

Qiang, Y., Huang, Q. and Xu, J. (2020) ‘Observing community resilience from space: Using nighttime lights to model economic disturbance and recovery pattern in natural disaster’, *Sustainable Cities and Society*. Elsevier Ltd, 57, pp. 102–115. doi: 10.1016/j.scs.2020.102115.

Saraswathi, S. A. and Allirani (2013) ‘Survey on Image Segmentation via Clustering’, in *International Conference on Information Communication and Embedded Systems (ICICES)*, pp. 331–335.

Sayad, Y. O., Mousannif, H. and Al Moatassime, H. (2019) ‘Predictive modeling of wildfires: A new dataset and machine learning approach’, *Fire Safety Journal*, 104, pp. 130–146. doi: 10.1016/j.firesaf.2019.01.006.

Simonyan, K. and Zisserman, A. (2014) ‘Very Deep Convolutional Networks for Large-Scale Image Recognition’. Available at: http://arxiv.org/abs/1409.1556 (Accessed: 27 July 2020).

Soleh, M., Arymurthy, A. M. and Wiguna, S. (2018) ‘CHANGE DETECTION IN MULTI-TEMPORAL IMAGES USING MULTISTAGE CLUSTERING FOR DISASTER RECOVERY PLANNING’, *Jurnal Ilmu Komputer dan Informasi*. Faculty of Computer Science, Universitas Indonesia, 11(2), p. 110. doi: 10.21609/jiki.v11i2.623.

Yu, M., Yang, C. and Li, Y. (2018) ‘Big data in natural disaster management: A review’, *Geosciences (Switzerland)*. MDPI AG. doi: 10.3390/geosciences8050165.