National College of Ireland

An Evacuation Route Model for Disaster Affected Area

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Introduction

- Natural disasters are major adverse events
- Natural disasters impact the infrastructure and environment of the affected areas causing
  - loss of shelter
  - food shortage
  - spread of infectious diseases
- Effective monitoring for immediate post disaster response help reduce
  - economic losses
  - fatalities

Source: National Geographic

Source: TipTopTens

Number of natural disasters in China in 2018
22

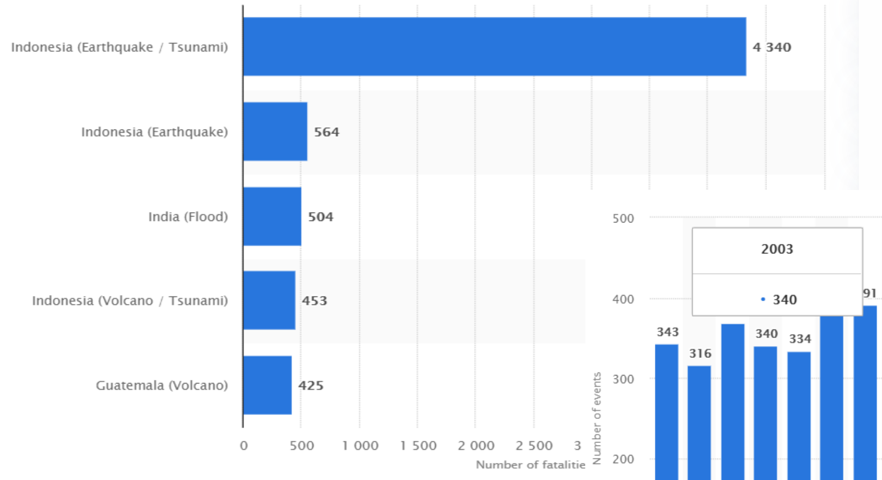
Share of fatalities from natural disasters in Asia in 2018
79.8%

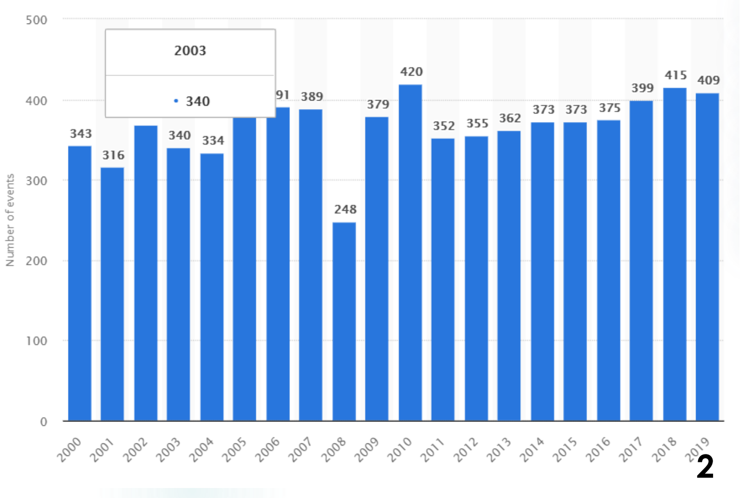
Share of natural disaster cost in the Americas
53 %

Type of natural disaster with most victims in 2018 - floods
34.2 million people

Most frequent type of natural disaster in 2018 - Flood
127

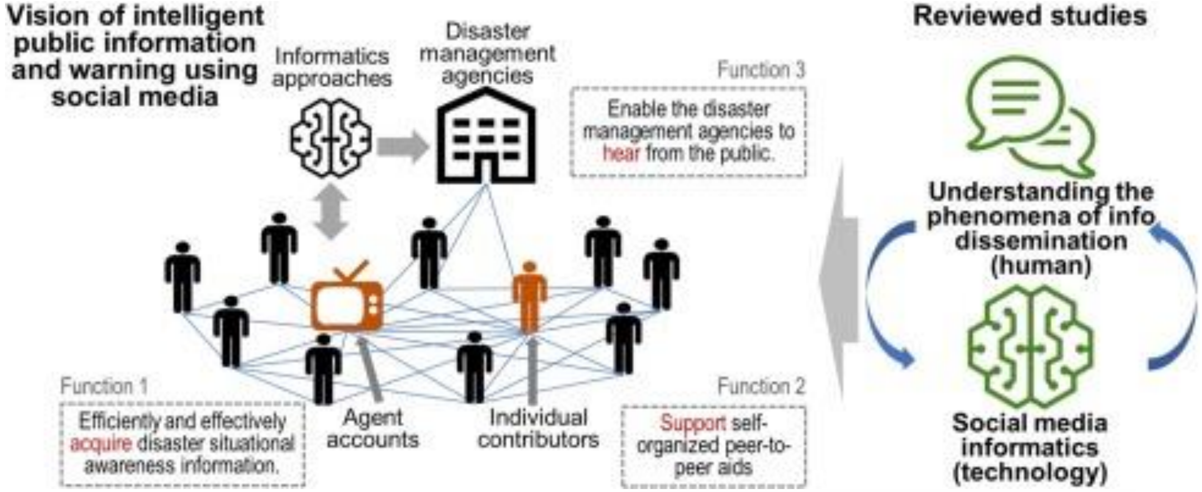
Cost of damages of storms in 2018
70.8bn USD





Introduction

- Models based on semantic analysis of real-time data extracted from social networks
  - sources unreliable
  - data scarce



Source: Zhang et al. (2019)

- Satellite images can assist in real-time with
  - detecting disaster affected areas
  - Identifying evacuation routes

Source: National Remote Sensing Center

Source: Geomatics World

Objectives

- Investigate to what extend satellite images can be used to help evacuation of people in a disaster affected area
- Propose a model detects and classifies the severity of disaster affected areas on satellite images and recommend the safest and shortest evacuation route to a rescue shelter

Evacuation Route Model

Pre-Disaster

Evacuation Route Model

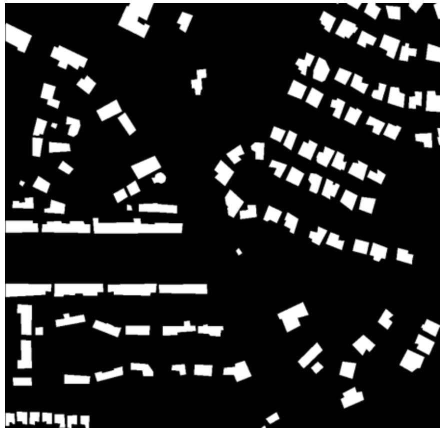
Pre-Disaster

Post-Disaster

Evacuation Route Model

Pre-Disaster

Segmentation Model

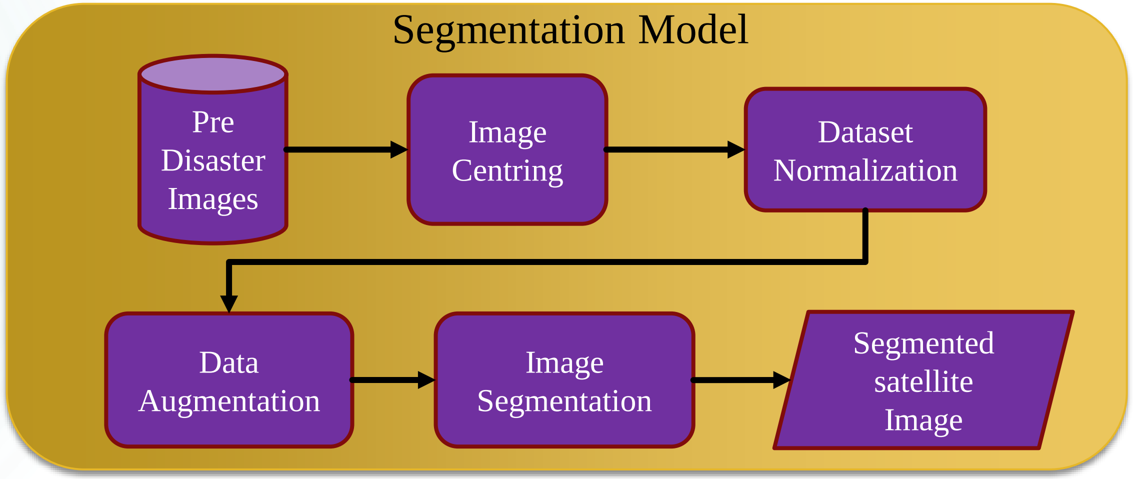


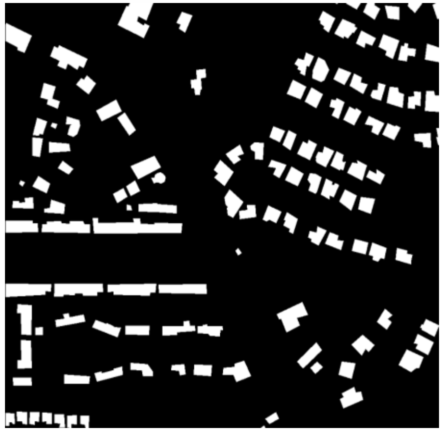
Post-Disaster

Segmentation Model

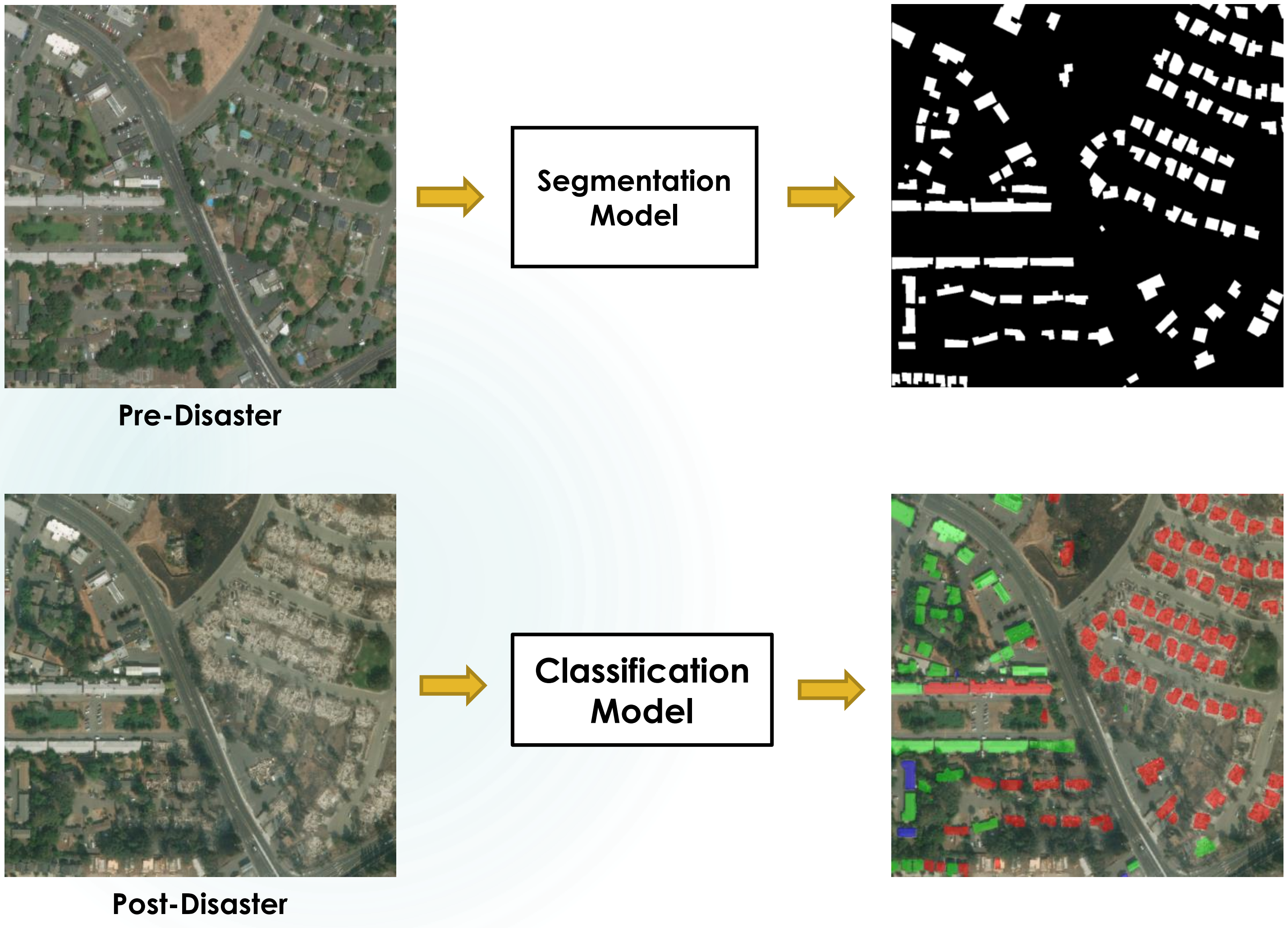
- Identifies buildings from the satellite images by classifying each pixel into either a **building** or a **background**
- Based on the **U-Net Architecture** (Ronneberger et al., 2015)
- Consist of contraction path and expansive path

Pre-Disaster





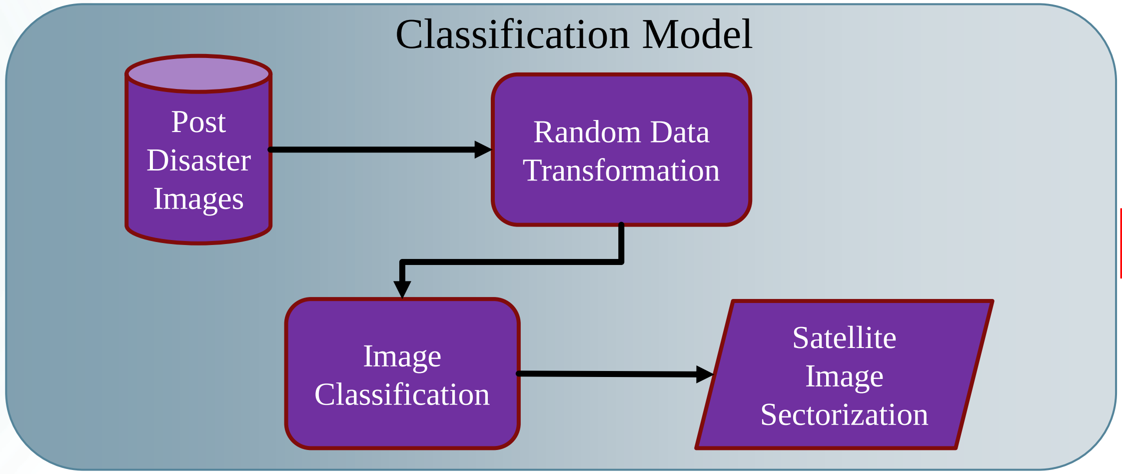
Evacuation Route Model



Classification Model

- Classify buildings into
  - *no-damage, minor-damage, major-damage, destroyed*
- Based on **ResNet50 Architecture** (He et al., 2016)

Post-Disaster



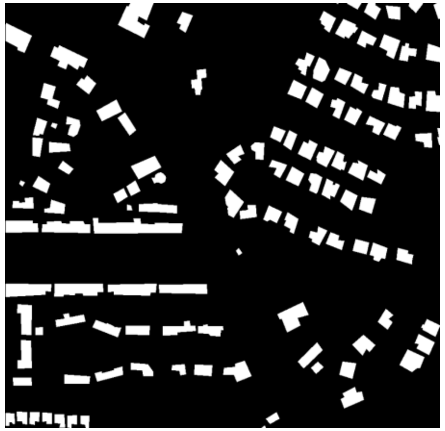
Evacuation Route Model

Pre-Disaster

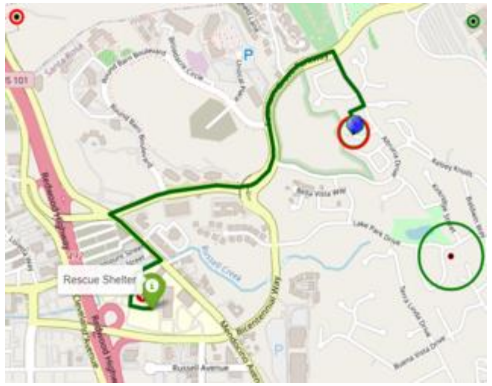
Post-Disaster

Segmentation Model

Classification Model

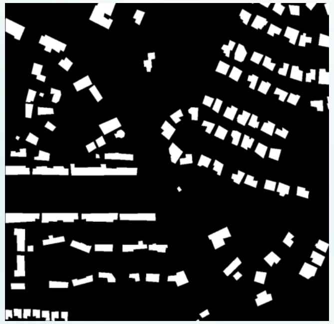


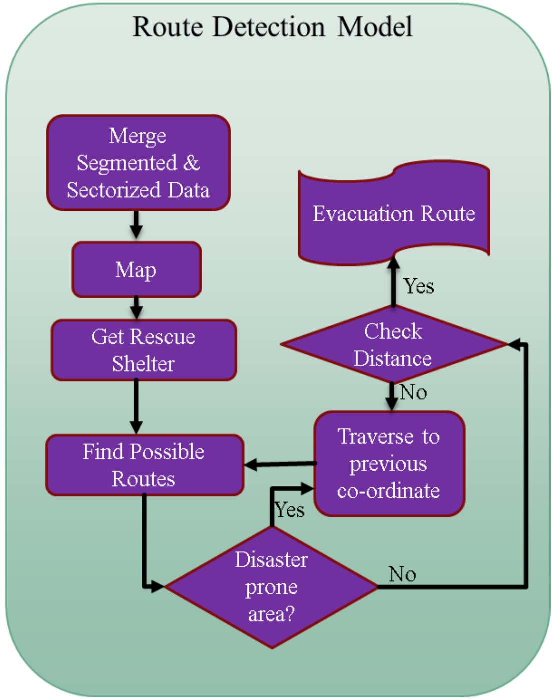
Route Detection Model

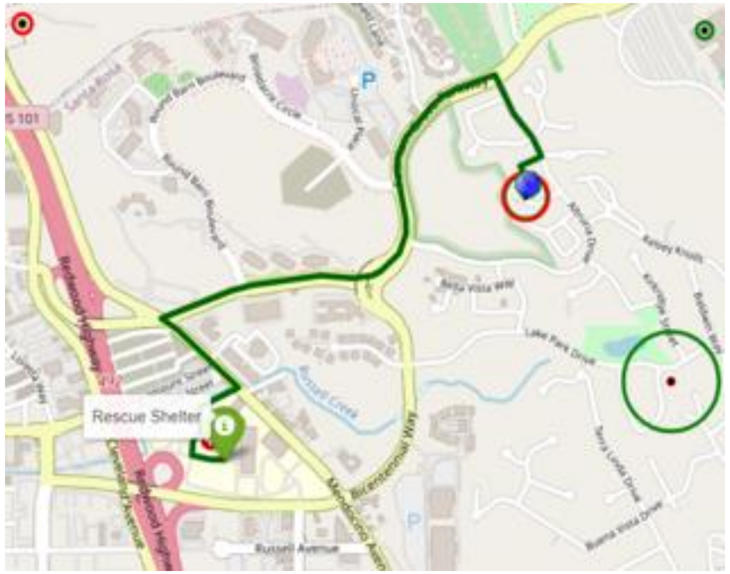


Route Detection Model

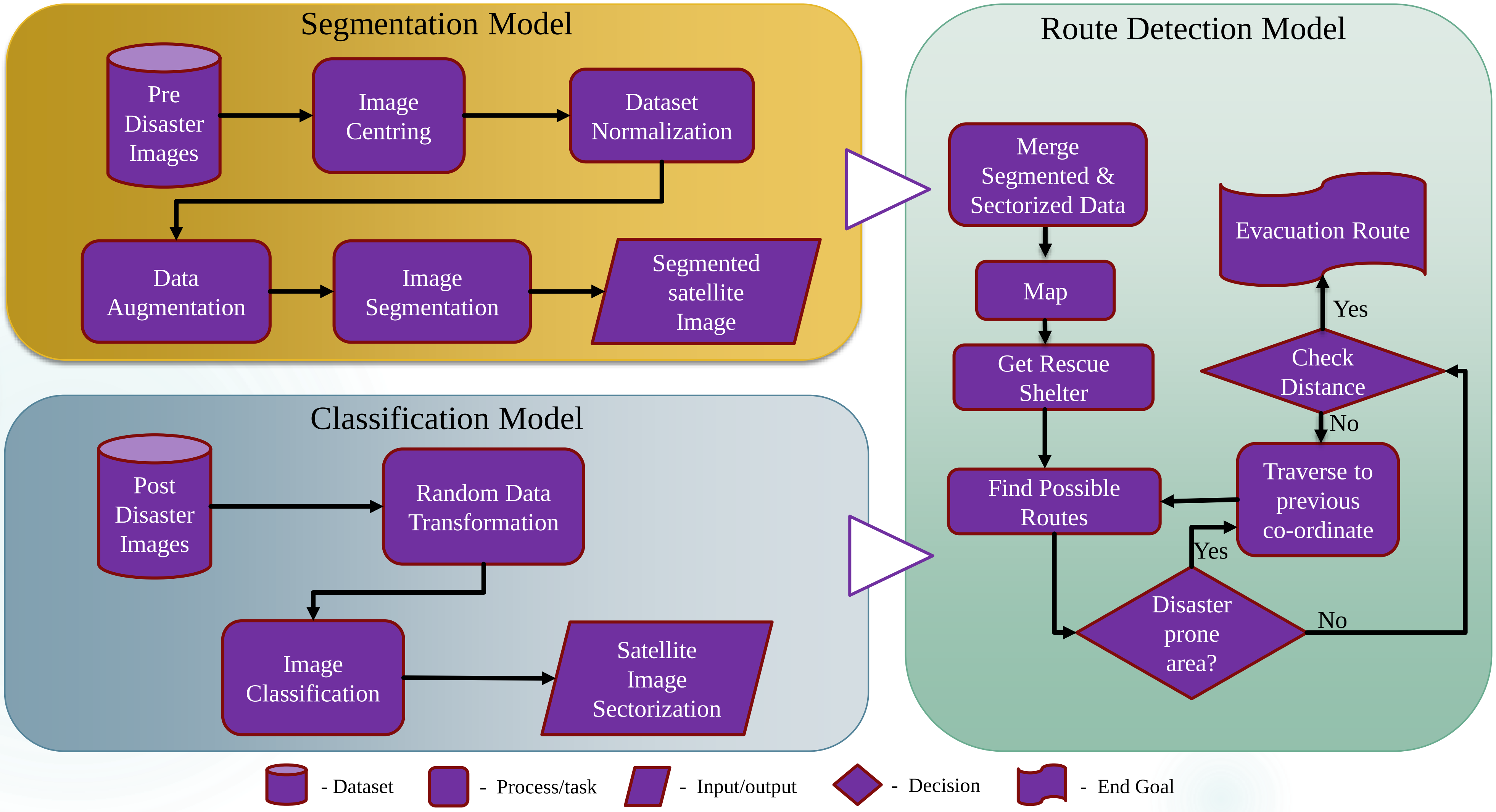
- Identify the shortest and safest route to a rescue shelter
- Based on **Dijkstra's algorithm** (Dijkstra, 1959)
- Rescue shelter is a hospital in the radius of 5 km



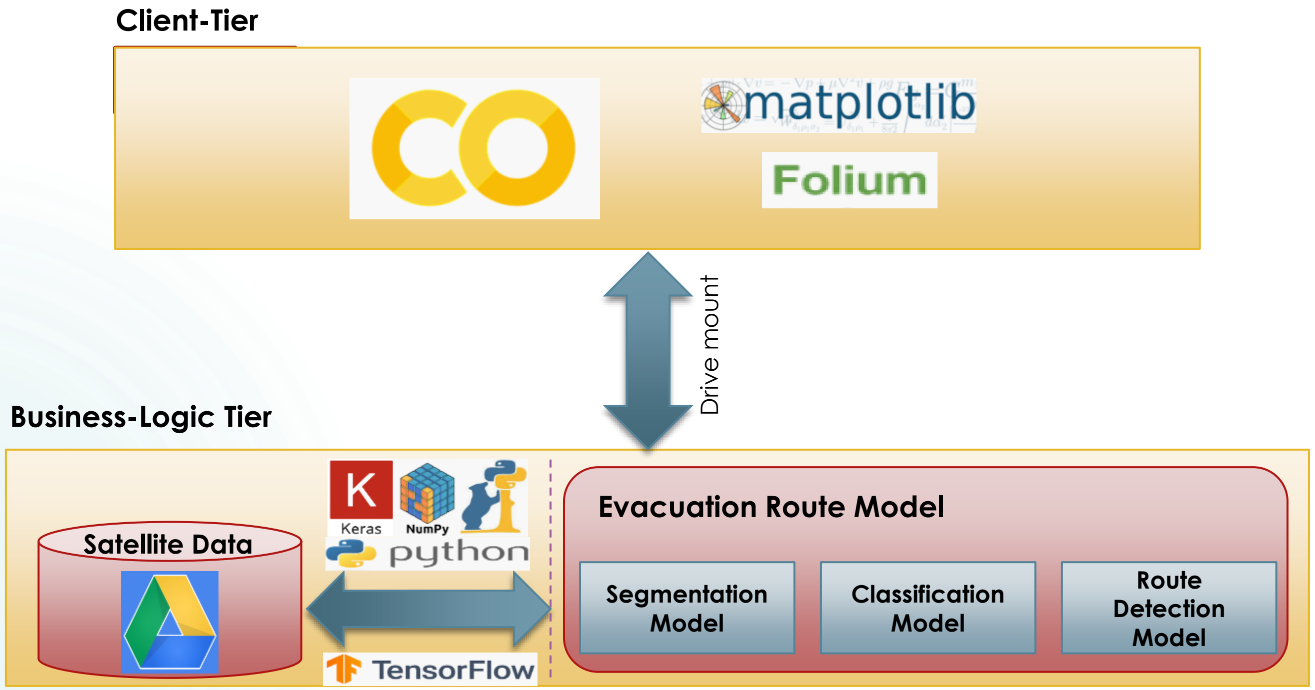




Evacuation Route Model



Technologies



Evaluation

- **Experiment 1: Segmentation Model**
  - Compare with Building Footprint Extraction (Pasquali et al., 2019)
  - Use F1-score and Intersection Over Union (IOU)
- **Experiment 2: Classification Model**
  - Compare with VGG16 and VGG19 models (Simonyan & Zisserman, 2015)
  - Use F1-score, Precision and Recall
- **Experiment 3: Route Detection Model**
  - Real-time data update
  - Capacity to adapt the evacuation route dynamically

XBD Dataset

- Pre-disaster and post-disaster high-resolution satellite imagery (Gupta et al., 2019)
- Contains 850,000 building polygons from six different types of natural disaster around the world, covering a total area of over 45,000 square kilometers
- Licensed under the Creative Commons Attribution-Noncommercial-ShareAlike 4.0 International (CC BY-NC-SA 4.0) license

Score	Label	Visual Description of the Structure
0	No damage	Undisturbed. No sign of water, structural damage, shingle damage, or burn marks.
1	Minor damage	Building partially burnt, water surrounding the structure, volcanic flow nearby, roof elements missing, or visible cracks.
2	Major damage	Partial wall or roof collapse, encroaching volcanic flow, or the structure is surrounded by water or mud.
3	Destroyed	Structure is scorched, completely collapsed, partially or completely covered with water or mud, or no longer present.

Segmentation Model

Model	F1-Score	IOU
Building Footprint Extraction	0.79	0.68
Segmentation Model	0.84	0.73

- **Wilcoxon Rank Sum Test**
  - *p*-value = 0.003383
- Rejects the null hypothesis with significance 0.05
  - IOU is greater than the Building Footprint Extract model

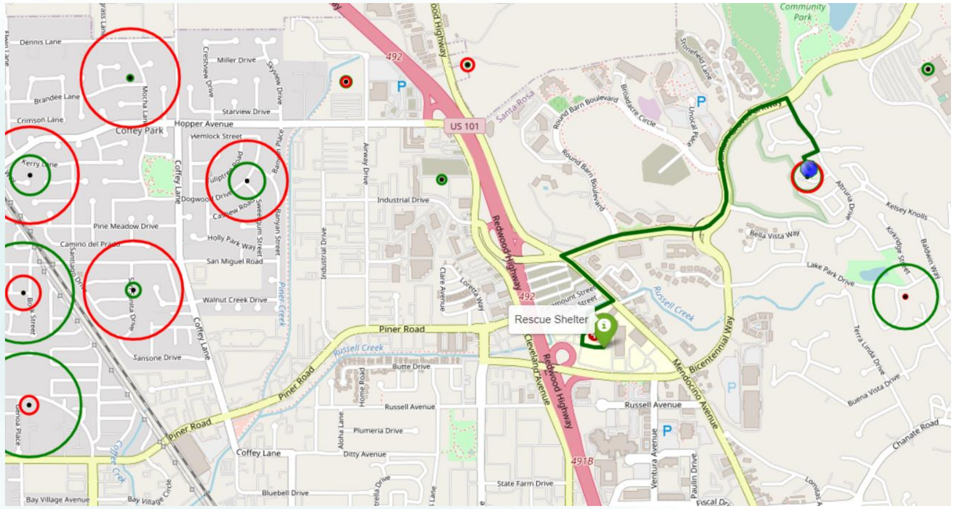
Classification Model

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

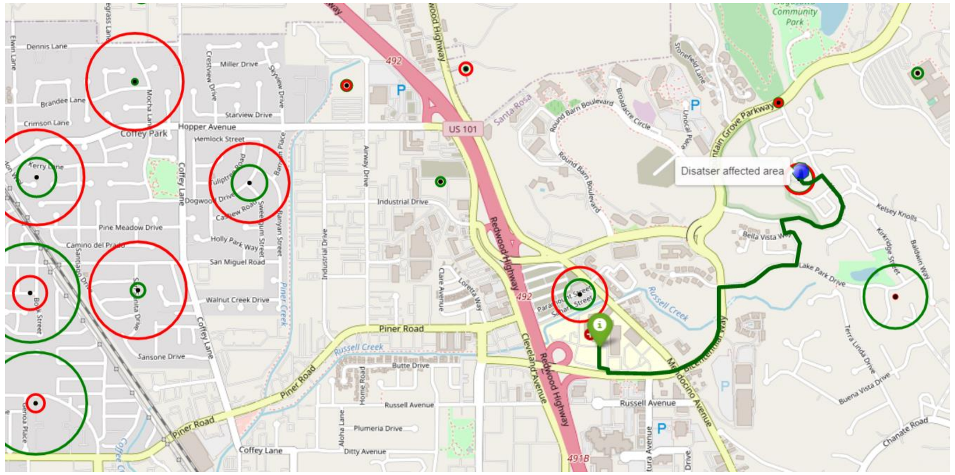
- Classification Model F1-score improves compared to VGG network models
- Classification Model is more balanced compared to VGG network models

Route Detection Model

Before disaster data update



After disaster data update



Conclusions

- Propose an Evacuation Route Model that uses satellite images to recommend the safest and shortest route to a rescue shelter
- The Evacuation Route Model is comprised of
  - The Segmentation model is 5% more accurate than the Building Footprint Extraction model
  - The Classification model is 8% and 10% more accurate than the VGG16 model and VGG19 models respectively
  - The Route Detection Model can dynamically adapt the safest and shortest route path to the rescue shelter due to the update of satellite images

Future Works

- Detect and classify the condition of roads in addition to buildings on satellite images
- Use A* instead of Dijkstra's algorithm
- Compare the Evacuation Route Model against other similar frameworks instead of their individual components
- Integration with post-disaster resource allocation systems
- Study the Ethical implications of these types of systems

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Thank You!!