Disaster Impact Prediction using Aerial Satellite Imagery

Group 30

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Introduction

- Predict the impact of a disaster using aerial satellite imagery
  - Identify hardest hit disaster affected regions
  - Prioritize and dispatch rescue units

- **What we have?**

  Pre and Post-disaster Satellite Images

- **What we need?**

  Disaster mapping from satellite images

Related Work

- Directly compare raw RGB values
  - Pixel values can be quite different even in areas with no disaster impact
  - Different season, lighting and other noise

- Using CNNs as a classifier
  - Detect damaged buildings
  - Rely on building relatively large training datasets for damaged areas
  - Not scalable

Related Work

From Satellite Imagery to Disaster Insights. Jigar Doshi, Saikat Basu, Guan Pang. 2018. https://arxiv.org/abs/1812.07033.

- Use only roads and building features while comparing
- CNN is used for segmenting the features
- CNN is not used directly to detect the damaged features

How we plan to extend ?

More features

Related Work

For Segmentation

Residual Inception Skip Network for Binary Segmentation. Jigar Doshi. 2018. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops.https://arxiv.org/abs/1812.07033.

- Models and their results (in mIoU)

Models	Single Model	Exp Avg	CLR
U-Net	58.1	59.0	59.2
DeepLab	58.3	59.3	59.4
ResInceptionSkip	60.1	61.2	61.3

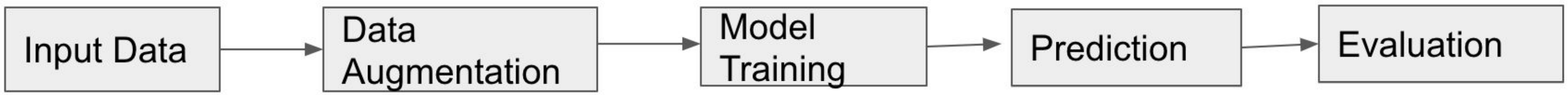
Dataset

- Low resolution M-band images are used
- M band(400-1040 nm), 1.24m/pixel, color depth 11 bit.
- The following features are more relevant for the disaster impact prediction task:
    - Buildings
    - Roads
    - Trees
    - Water
    - Crops

Image Pre-processing

- Image augmentation
  - converted 24 images to 4000 images
- Random transformations are applied across patches extracted from images
  - reversing first dimension
  - mirroring along both dimension

Project Pipeline



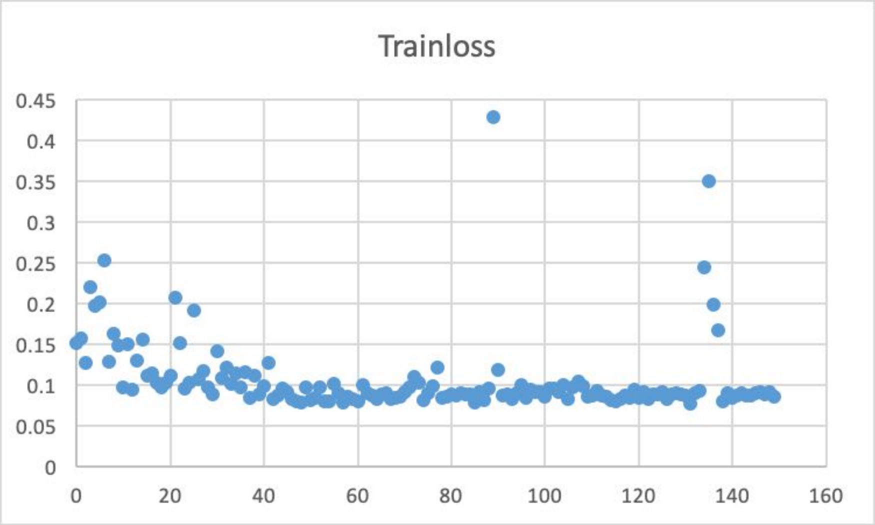
Training

- Unet Architecture
  - Encoder - 5 Convolutional blocks
  - Decoder - 5 Transpose Convolution blocks
- Optimiser
  - Adam
- Loss
  - Weighted Binary Loss Cross Entropy

Training

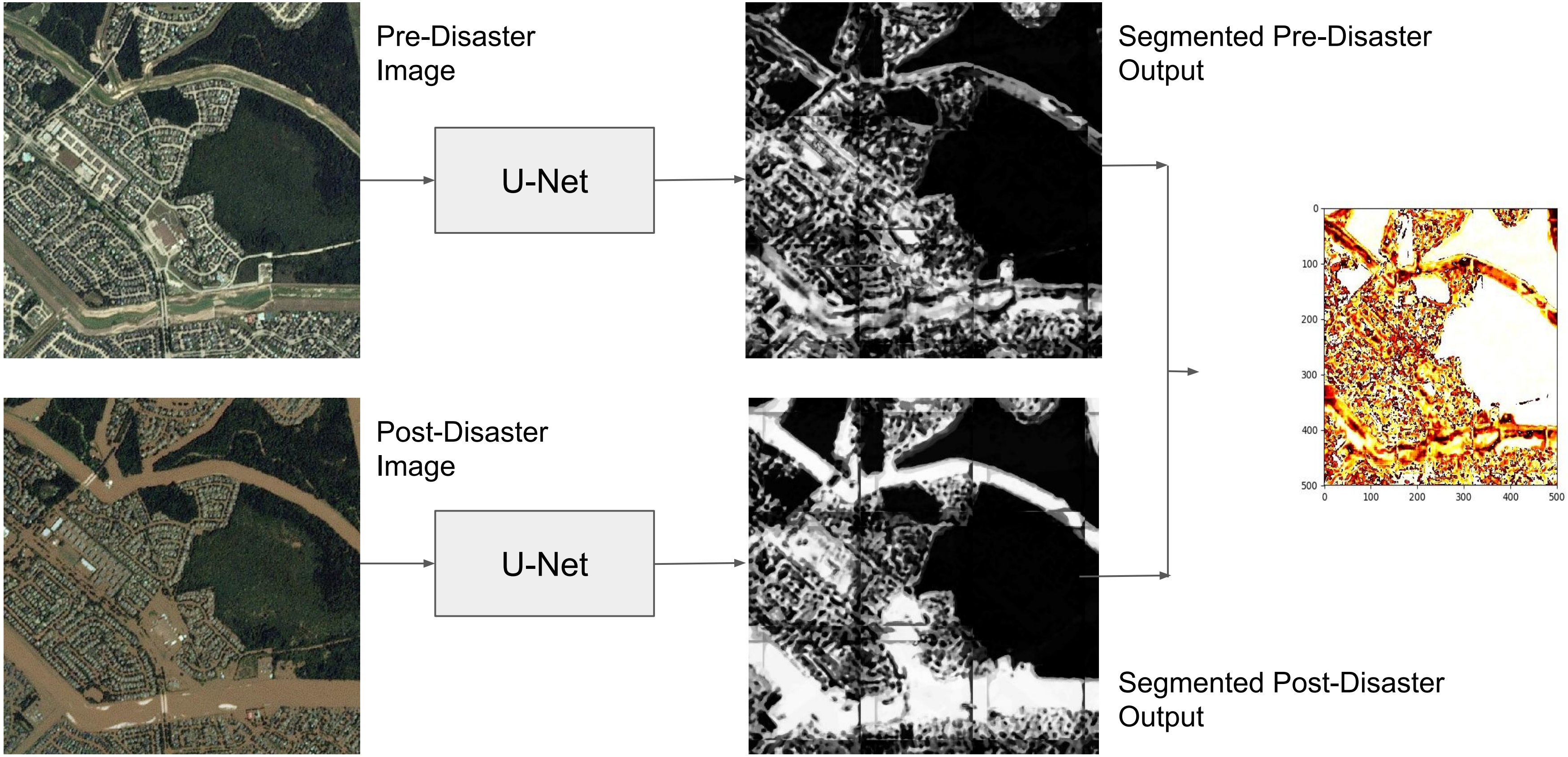
Training Environment	Google Cloud Platform
Cloud Configuration	1. 52 GB RAM 2. 8 vCPUs
Training Hours	~40 hrs
No of Epochs	150 epochs

Training

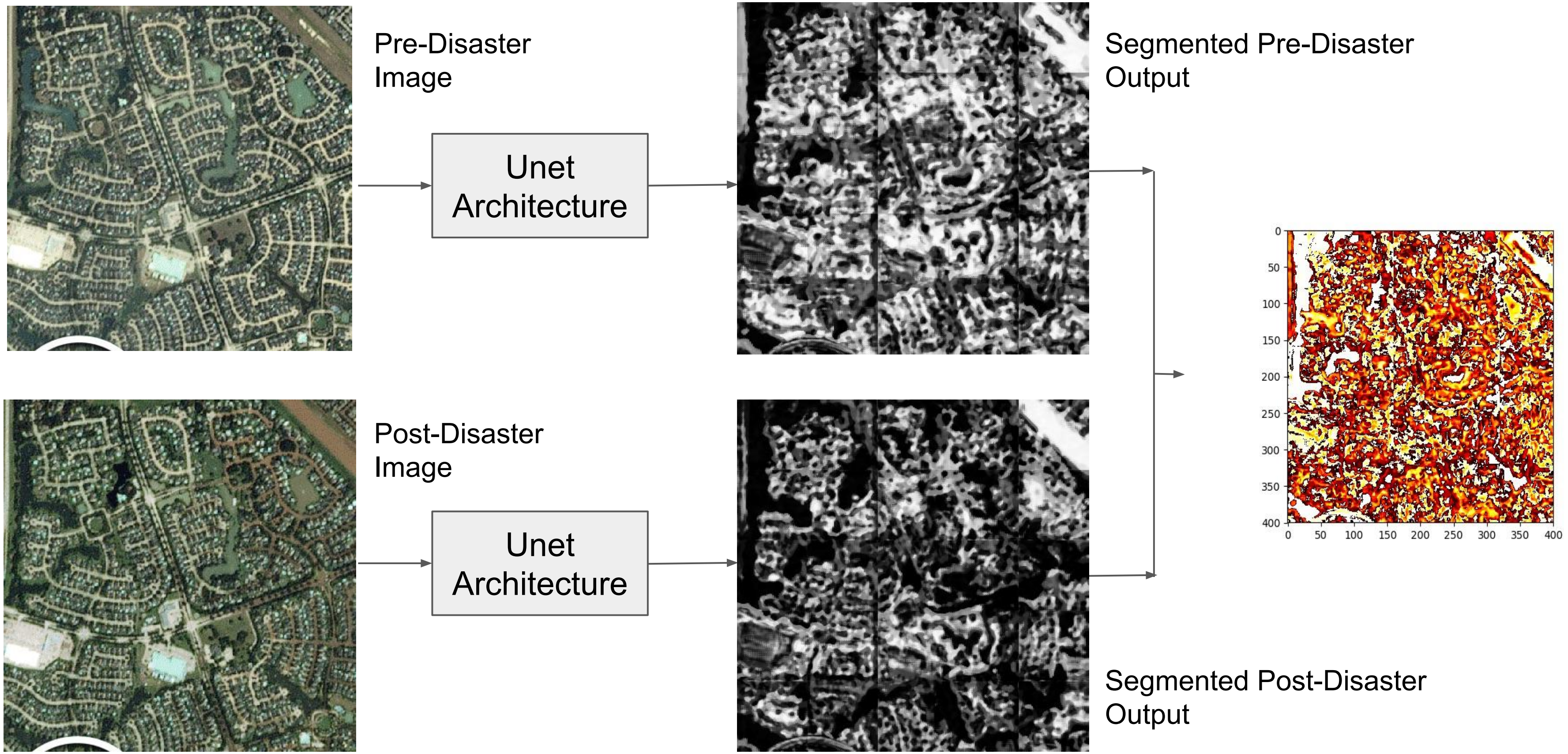


- Train loss and Validation loss plotted per epoch.
- Save the best model weights.

Disaster Prediction



Disaster Prediction

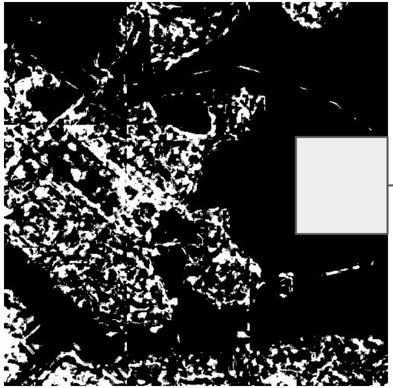


Evaluation

Metric : Disaster Impact Index (DII)

$$\text{Disaster Impact Index}(DII) = \Delta Pred = \frac{\left|\eta_{Pred_{before}=1 \& Pred_{after}=0}\right|_{grid}}{\frac{1}{N_{grid}} \sum_{i=1}^{N_{grid}} \left|\eta_{Pred_{before}=1}\right|_{grid_i}}$$

Metric F1 = ~71%



Grid of size
20*20

Conclusion

- In this project, we perform CNN-based semantic segmentation on satellite imagery obtained before and after disaster to identify areas of maximal damage.
- Our work incorporates high-level features including roads,buildings,trees,crops and water. This renders increased flexibility to proposed model over existing approaches.
- Our experiments show a high correlation between predicted impact areas and human –annotated ground truth labels.