UE17CS490B – Capstone Project Phase – 2

SEMESTER - VIII

END SEMESTER ASSESSMENT

Project Title : Natural Disaster damage assessment using Image Segmentation by Deep Learning
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Abstract

When a disaster strikes, quick and accurate situational information is critical to an effective response. Before responders can act in the affected area, they need to know the location, cause and severity of damage.

Satellite imagery can provide unbiased overhead views, but raw imagery is not enough to inform recovery efforts. High-resolution imagery is required to see specific damage conditions, but because disasters cover a large ground area, analysts must search through huge swaths of pixel space to localize and score damage in the area of interest. Then annotated imagery must be summarized and communicated to the recovery team. It is a slow and laborious process.

To accelerate the development, we propose a deep learning based semantic image segmentation algorithm called U-Net, which is at pixel space with very high accuracy and efficiency. This U-Net architecture is built upon the Fully Convolutional Network and modified in a way that it yields better segmentation in imaging.

Team Roles and Responsibilities

1. Bhoomika S	Model Architecture	Data Augmentation	Training
2. Pushpender Singh	Data Collection	Data Preprocessing/ Augmentation	Testing
3. Keshav Agarwal	Data Collection	Data Preprocessing/ Augmentation	Testing
4. Aditya Shankaran	Model Architecture	Data Augmentation	Training

Summary of Requirements and Design

- Hardware Requirements:
  - -Windows 10
  - -Hard Disk 256 GB
  - -RAM 8GB
  - -Graphic Card 2GB

- Software Requirements:
  - -Python 3.5
  - -OpenCV Library
  - -TensorFlow
  - -NumPy
  - -Keras

- Applications of Python
- NumPy
- Image Processing

UNET Architecture Design & Training

- The UNET was developed by Olaf Ronneberger et al. for Bio Medical Image Segmentation.
- The architecture contains two paths. First path is the contraction path (also called as the encoder) which is used to capture the context in the image. The encoder is just a traditional stack of convolutional and max pooling layers.
- The second path is the symmetric expanding path (also called as the decoder) which is used to enable precise localization using transposed convolutions.
- Thus it is an end-to-end fully convolutional network (FCN), i.e. it only contains Convolutional layers and does not contain any dense layer because of which it can accept images of any size.

In the original paper, the UNET is described as follows:

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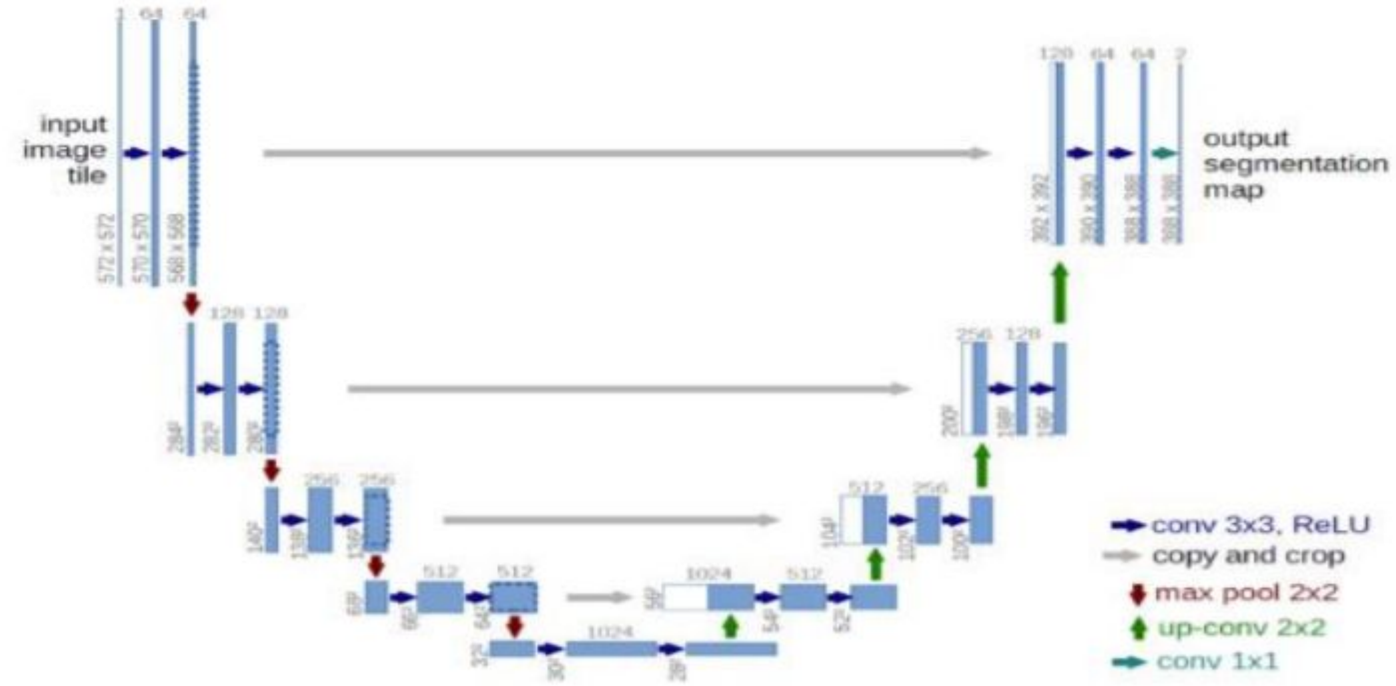
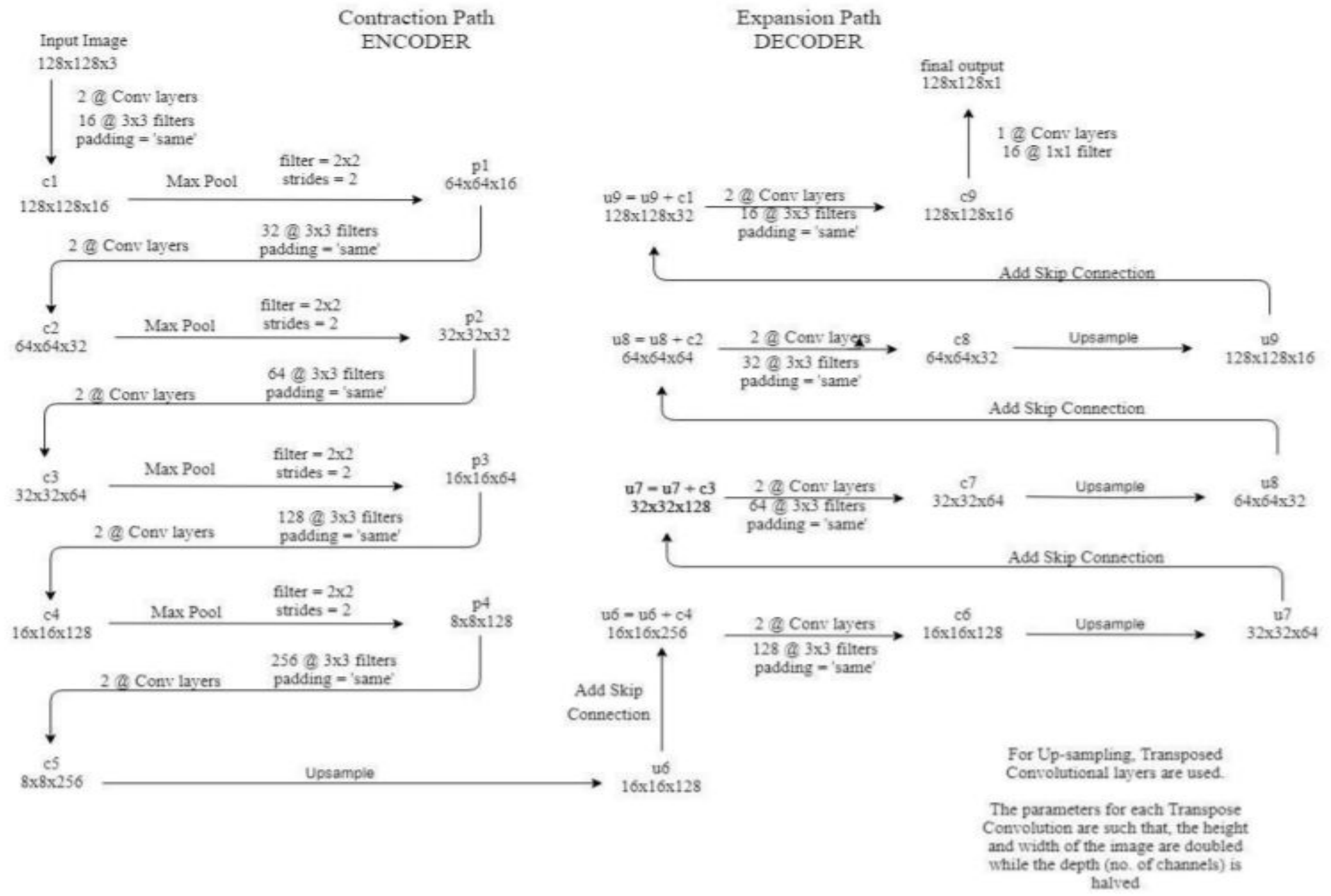


Fig. 1. U-net architecture (example for 32x32 pixels in the lowest resolution). Each blue box corresponds to a multi-channel feature map. The number of channels is denoted on top of the box. The x-y-size is provided at the lower left edge of the box. White boxes represent copied feature maps. The arrows denote the different operations.

5.a U-Net Architecture

Below is the detailed explanation of the architecture:



5.b Detailed U-NET Architecture

Design Constraints, Assumptions & Dependencies

- Availability of datasets.
- Deploying deep learning model into hardware platforms having below constraints:
  - ➢ Limited computational resources (CPU and GPU)
  - ➢ Limited memory
- U-Net algorithm is best suited for image segmentation.
- Dependent on the tensorflow deep learning framework.
- Quality of the dataset may affect the accuracy.
- Boundary parts sometimes of some labelled images are not too sharp, but this can be solved by using large dataset or by applying CRF (Conditional Random Fields).
- U-Net algorithm enhancement and training on hardware to achieve desired accuracy and speed in the given timeline.
- Hyper-parameters tuning is a time taking process.

Summary of Methodology / Approach

Basic Approach and Results obtained

Our adopted U-Net architecture originated from Ronneberger *et al.*, U-Net network structure which was originally put forth to solve biomedical imaging problems.
With growing technologies in deep learning, latest residual networks and Batch Normalization(BN) are being introduced into the study and enhancement of the U-Net network system. We will be using these latest introduced technologies into our network system.

Summary of Methodology / Approach

Need for Changing the approach:

- There is currently no complications proceeding with our approach since the deep learning based U-Net architecture that is being used has proven to be highly efficient for smaller set of dataset.
- It achieves highest accuracy at pixel-level.
- The model can perform well under extreme weather conditions as well.
- The system can be easily deployed in various softwares since the memory requirement is very low as compared to other models.

Summary of Methodology / Approach

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Details of new approach

The U-Net architecture adopted in our study is tuned slightly different from the original U-Net architecture.

- Batch Normalization(BN) is introduced to accelerate the training reducing the issue of internal covariate shifting. Every minibatch input is normalized using the mean or variance of the minibatch and is again denormalized with a learned bias and scaling factor(weights).

- In each layer only two convolutions are performed which showed better accuracy in predicting the masks.

- Each convolution is followed by a batch normalization and max-pooling is introduced at the end of every layer.

- The last convolution in the decoder phase is activated using sigmoid function which tends to pull the values towards 0 or 1 based on positive or negative values of the pixels giving us the 2 distinct classes of the mask.

Design Approach

Our adopted U-Net architecture is originated from Ronneberger et al., U-Net network structure which was originally put forth to solve biomedical imaging problems.

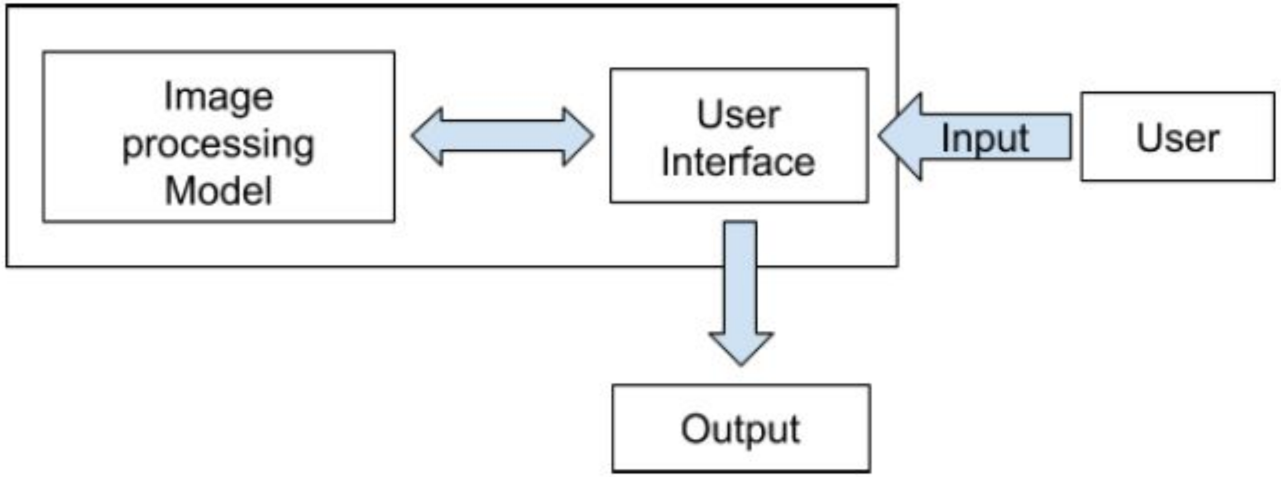
- U-Net is more successful than conventional models, in terms of architecture and in terms of pixel-based image segmentation formed from convolutional neural network layers.
- Works efficiently on small datasets through heavy data augmentation as in some cases the number of annotated samples will be less.
- Works for binary as well as multiple classes.
- It is scale-invariant.

- Can be used in a multitude of applications like Object Detection/Segmentation, GANs, etc.
- The network does not have a fully-connected layer. Only the convolution layers are used.
- The features extracted at different levels in the contracting path are then combined with the feature maps in the expansion path giving rise to more number of features which is necessary for an accurate segmentation map.

Alternate Design Approaches like PSPNet, ResNet, Deeplab, SegNet, ICNet were considered but on comparing U-Net outperformed the rest in various parameters.

Design Description

High Level System Design

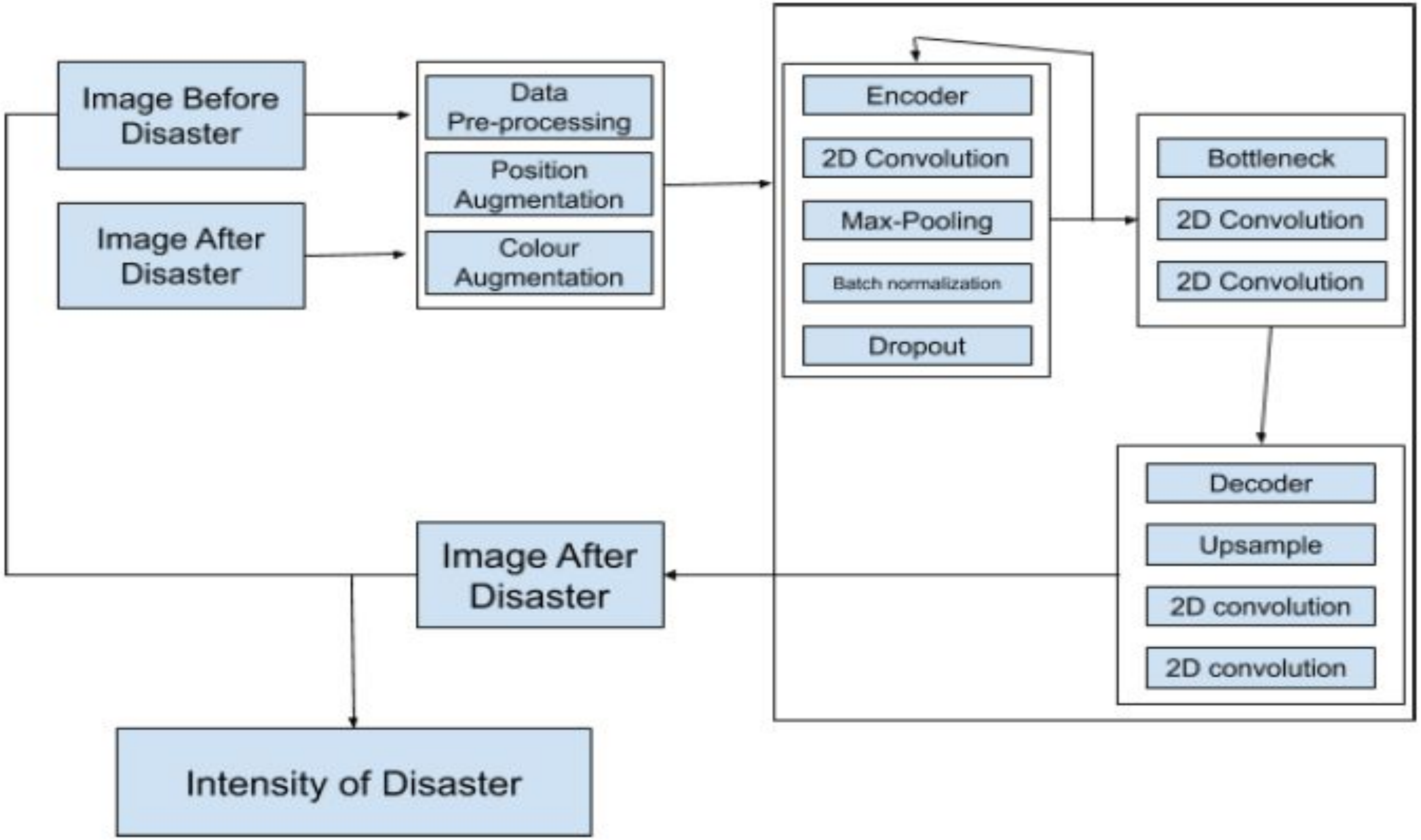


The chief users are Disaster Management Organisations:

- The aerial images of disaster prone areas before and after the disaster are fed into the system which gives the intensity of the disaster that has affected the place.
- This data is used by the organisations to adopt preventive measures to avoid any casualties in late future.
- Machine learning model used to build our system is based on U-Net architecture.

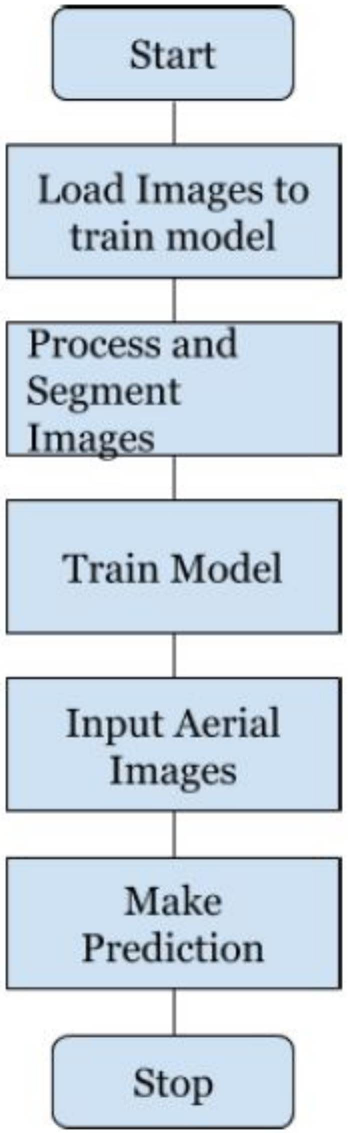
Design Description

Master Class Diagram



Design Description

Swimlane Diagram



Characteristics and Implementation

- We propose a U-Net-Architecture model for damage classification and building segmentation.
- One element of this architecture is a U-Net model that analyses a single input image and produces a segmentation mask showing building locations in the input image.
- The U-Net model is a fully convolutional network that was proposed for image segmentation. Besides its encoder-decoder structure for local information extraction, it also utilizes skip connections to retain global information. A single U-Net model analyses input frames IA and IB, which depict the same scene pre-disaster and post-disaster, respectively.
- Since the U-Net focuses on the building segmentation objective, it is agnostic to the disaster. In other words, we can use the same model for both pre-disaster and post-disaster images to produce binary masks IMA and IMB, corresponding to their respective input frames.

Walkthrough

Demo and Product walk thru

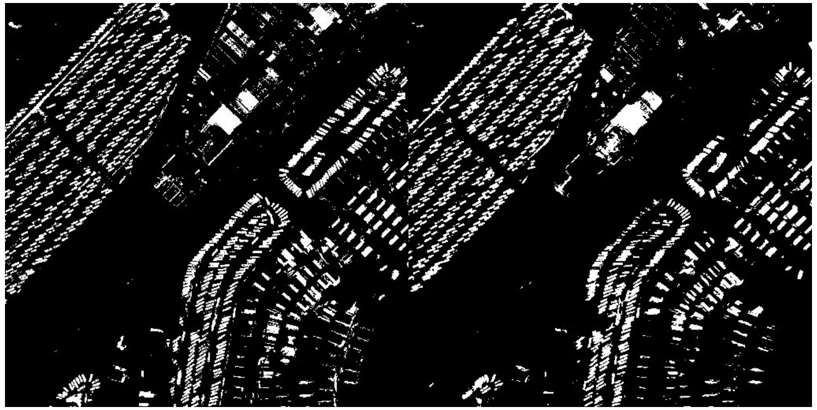
Results and Discussion

Results

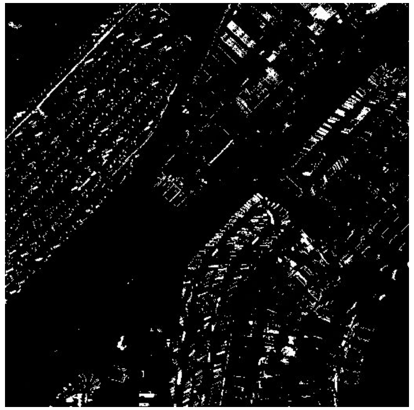
● The images before and after the disaster was segmented accurately and the percentage of damage was shown.
● One example is given below:
on the left is before disaster and on the right is after disaster

Input images

Enhanced images



Segmented images



Regions affected

Documentation

Show the evidences, status of the below documents:

- Project report finalized by Guide?
- IEEE (similar) Format of Paper ready for submission or current status? Which Conferences are you targeting?
- Video (2-3 minutes) of your project? Please Play.
- Add the Github repository link.
- A3 size Poster of your project to be shown.
- All artifacts of your project uploaded in the CSE Project repository?

Lessons Learnt

Segmentation results can be made more accurate and color based segmentation for the intensity of the damage can be presented along with the type of disaster identification.

Due to limitation in the hardware requirements we had to train the model in our local PC with a large dataset ~25GB

This slowed down our progress but we handled it by analyzing the loss and accuracy graphs while training our U-Net model.

Conclusion and Future work

We presented a Siam-U-Net-Attn model with self-attention for building segmentation and damage scale classification in satellite imagery. The proposed technique compares pairs of images captured before and after disasters to produce segmentation masks that indicate damage scale classifications and building locations. Results show that the proposed model accomplishes both damage classification and building segmentation more accurately than other approaches with the xView2 dataset

References

[1] Rehman, Syed & Hussain, Mohameed. (2018). Fuzzy CMeans Algorithm Based Satellite Image Segmentation. Indonesian Journal of Electrical Engineering and ComputerScience.9.332-334. 10.11591/ijeecs.v9.i2.pp332- 334.

[2] Senthil Nathan, 2017. K-Means Algorithm based Satellite Image Segmentation. Journal of Engineering and Applied Sciences, 12: 7995-7997.

[3] Maria Vakalopoulou, Konstantinos Karantzalos, Nikos Komodakis, Nikos Paragios. Building detection in very high resolution multispectral data with deep learning features. Geoscience and Remote Sensing Symposium (IGARSS), 2015 IEEE International, Jul 2015, Milan, Italy. pp.1873-1876, ff10.1109/IGARSS.2015.7326158ff. ffhal01264084f

[4] Rejaie A., Shinozuka M., Reconnaissance of Golcuk 1999 Earthquake Damage Assessment with Satellite Images, Journal of Aerospace Engineering, 2004: 17, 1.

[5] Ehrlich D. ,Guo H.D.,Molch K., Ma J.W. Pesaresi M., 2009, Identifying damage caused by the 2008 Wenchuan earthquake from VHR remote sensing data, International Journal of Digital Earth.

References

[6] Li, N., Liang, X., Li, X., Wang, C., Wu, D., 2009, Network Environment and Financial Risk Using Machine Learning and Sentiment Analysis, Human and Ecological Risk Assessment, 227–252

[7] Anderson CL and Davison, M, 2009, The Application of Cash-Flow-atRisk to Risk Management in a Deregulated Electricity Market, Human and Ecological Risk Assessment, 253 – 269

[8] Choi Y. and Li, EY, 2009, Optimizing Risk Management for the Sustainable Performance of the Regional Innovation System in Korea through Metamediation, Human and Ecological Risk Assessment, 270- 280 [12] Wei J., Zhao,D., Wu, D., and Lv, S., 2009, Web Information and Social Impacts of Disasters in China, Human and Ecological Risk Assessment, 15: 281–297

[9] O. Benarchid and N. Raissouni, Support Vector Machines for Object Based Building Extraction in Suburban Area using Very High Resolution Satellite Images, a Case Study: Tetuan, Morocco, IAES International Journal of Artificial Intelligence (IJ-AI), Vol. 2, No. 1, March 2013, pp. 43 50.

[10] DibyaJyoti Bora (September, 2014) “A Novel Approach Towards Clustering Based Image Segmentation”, IJESE, Volume-2 Issue11, pp 6-10

Thank
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