Building Damage Classification

Team:
Masters of Disasters

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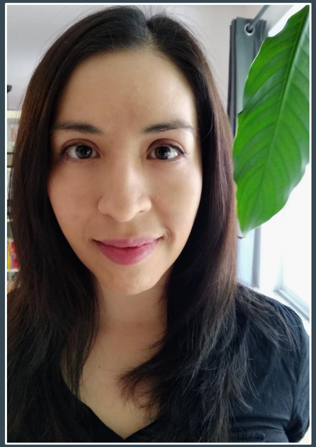

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Technical Translator

Problem statement

After a natural disaster occurs

- Fast and efficient resource allocation, aid routing, rescue, and recovery are needed
- General practice is to perform damage assessment in-person

Our objective

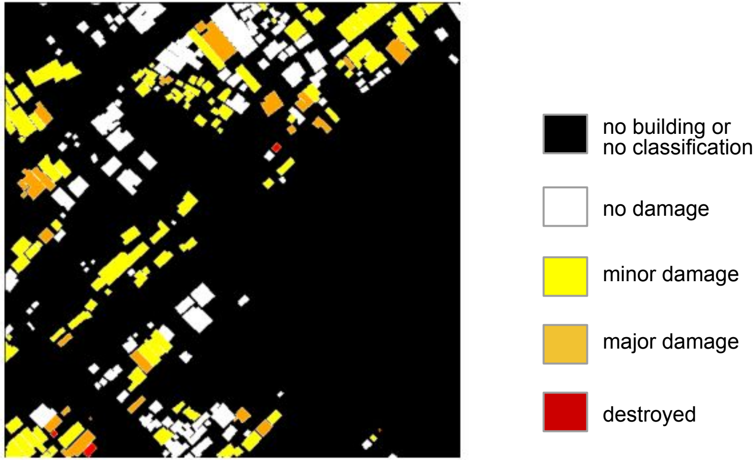
- Accurate building damage assessment after natural disasters by using aerial images and deep learning

Data product

Pre-disaster image*

Post-disaster image*

Building damage classification



Potential users: disaster response teams, government agencies among others

**Hurricane Matthew*

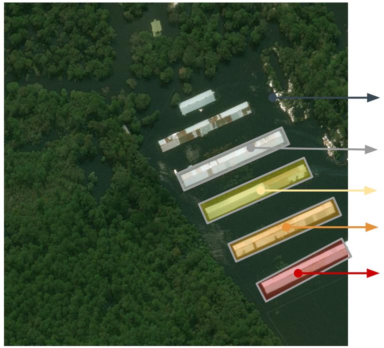
Introduction to Building Damage Dataset

Pre-disaster image*

Building coordinates
from pre-disaster images

Post-disaster image*

Damage label per
building from
post-disaster images



example labels:

not building/ unclassified

no damage

minor damage

major damage

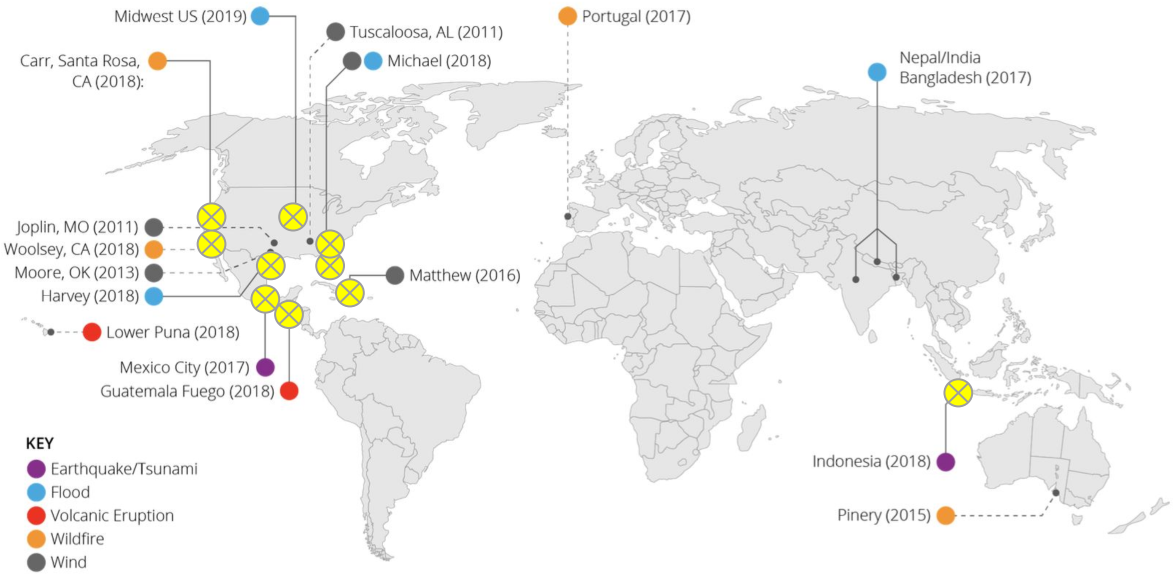
destroyed

**Florence - Hurricane*

Introduction to the Building Damage Dataset

Subset used in this project had:

- 10 different disasters
- 6 disaster types
- 1,353 pairs of images
- More than 100,000 buildings



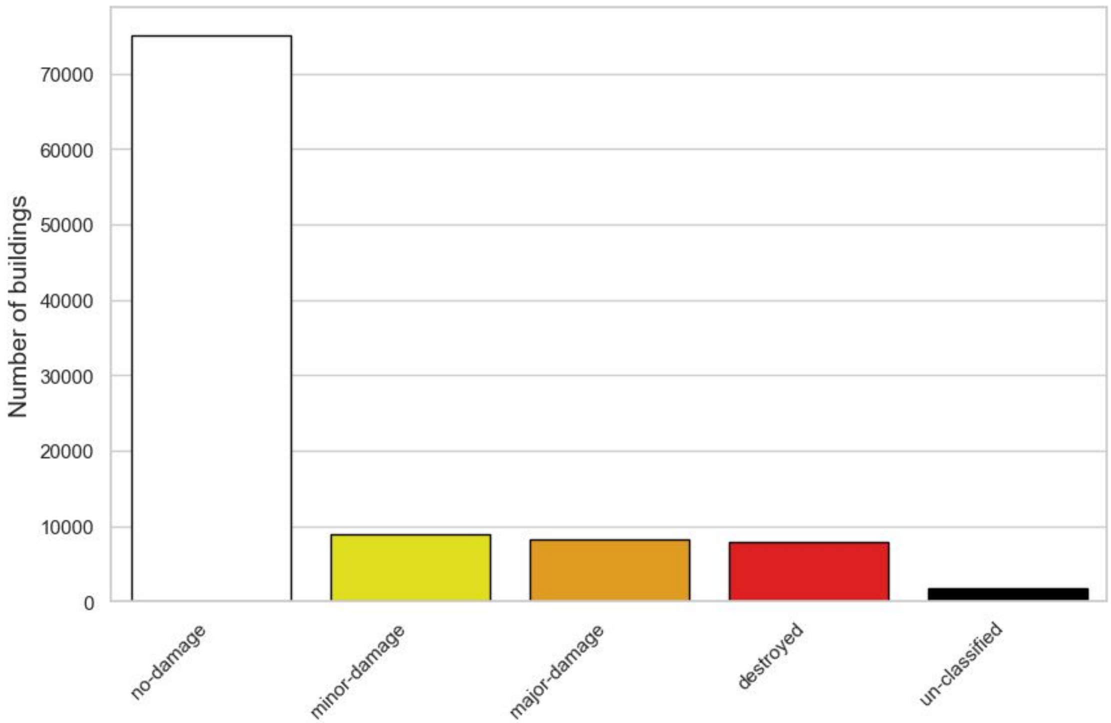
Joint damage scale

- Four different categories describing disaster damage level (degree of destruction)
- Damage level is valid for multiple disaster types
- Damage assessment manually created from satellite imagery and revised by NASA, CAL FIRE, FEMA, and the California Air National Guard teams.

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.

Gupta et al., 2019

Damage level distribution for our subset of data



Damage Classification Approach

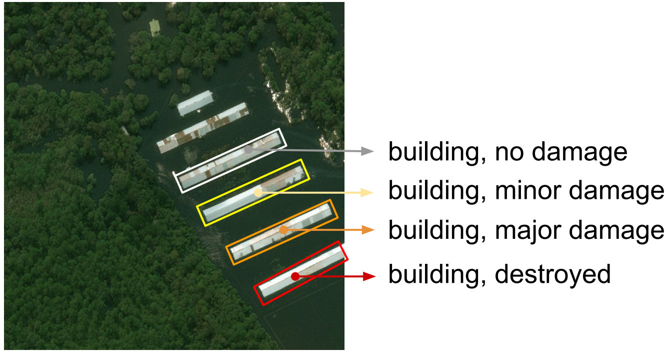
Image Labeling

Each image gets a label

building

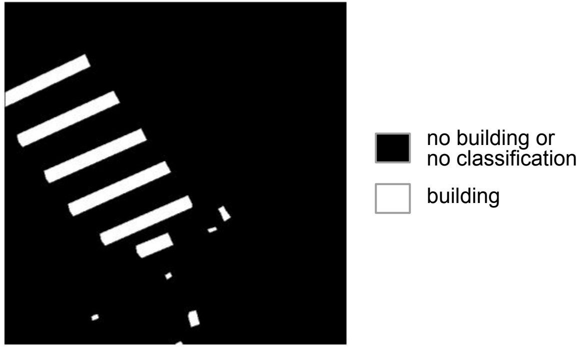
Object Detection

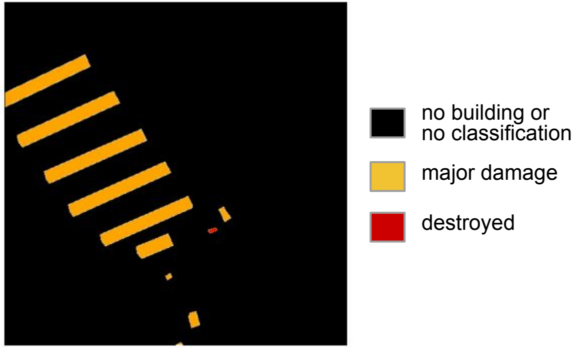
Boxes manually drawn around the objects get label



Semantic Segmentation

Each pixel in the image gets a label

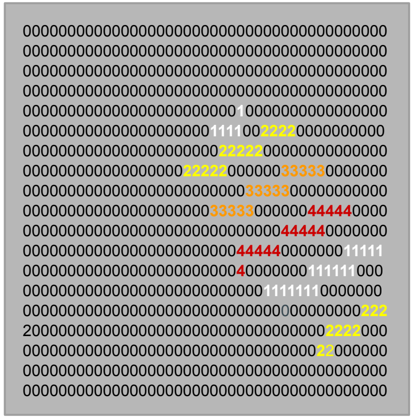




Baseline Model: SegFormer-b0 (Model 1)

Original image

Pixel classification



- SegFormer-b0 is a pre-trained semantic segmentation model

- ImageNet-1k subset has:
  - 1,000 object classes
  - 1,281,167 training images
  - mostly animal images

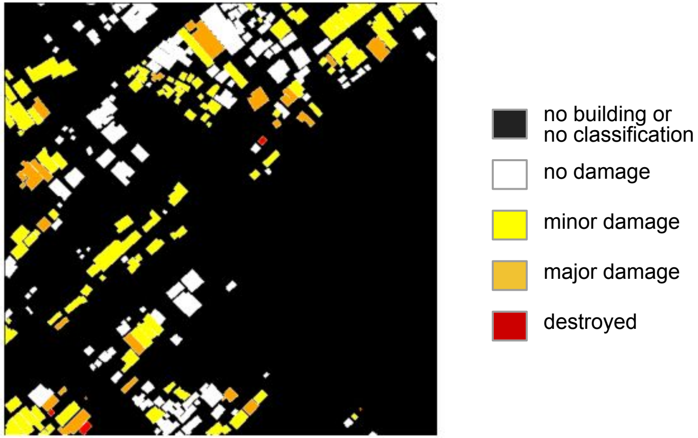
Training Scheme of Model 1

Basic approach: Reduce the complexity by only feeding the model with post-disaster images
Small subset of the original data + 10 training iterations

INPUTS FOR THE MODEL

Post-disaster image*

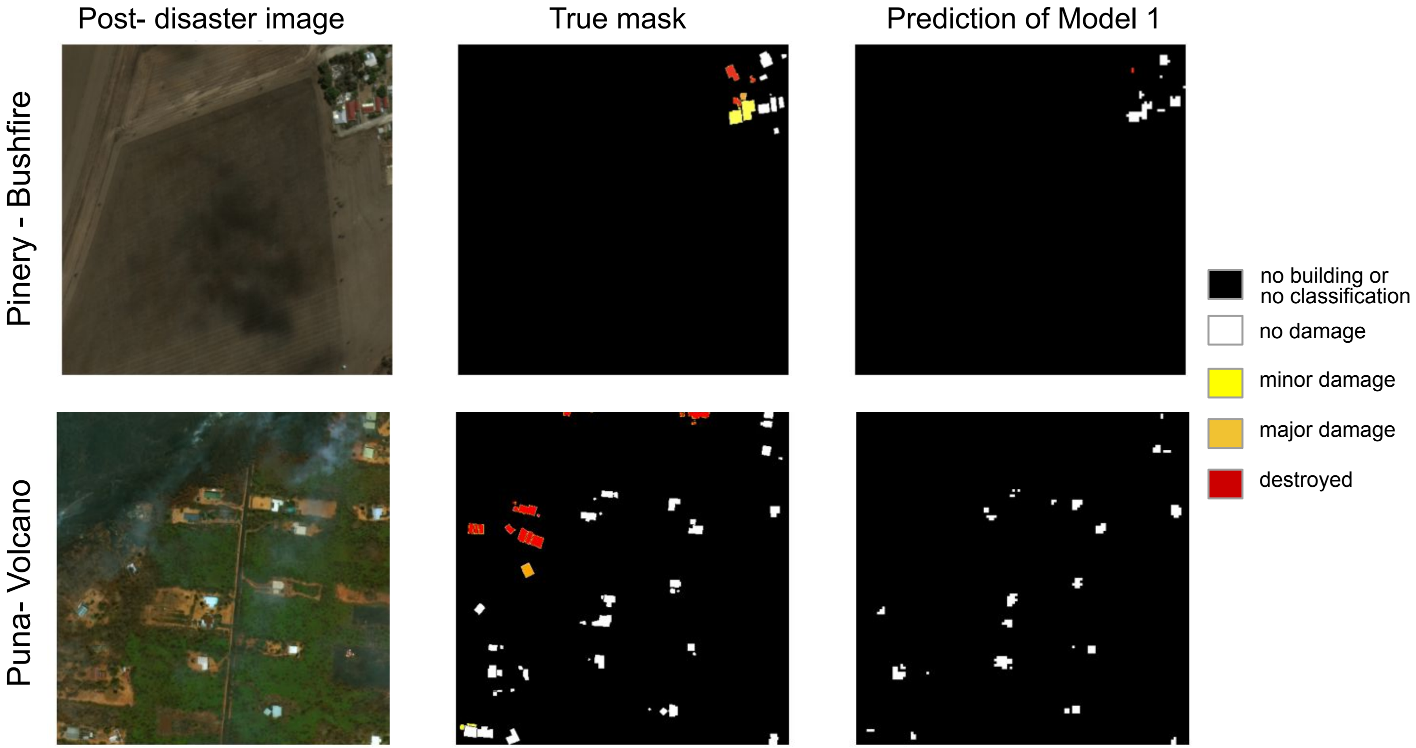
Building damage classification



Matthew - Hurricane

Model 1 Results

Test set: The model was trained on the same type of disasters at different locations



Class	F1 score - Pinery Bushfire
No building	0.99
No damage	0.39
Minor damage	0.00
Major damage	0.00
Destroyed	0.03

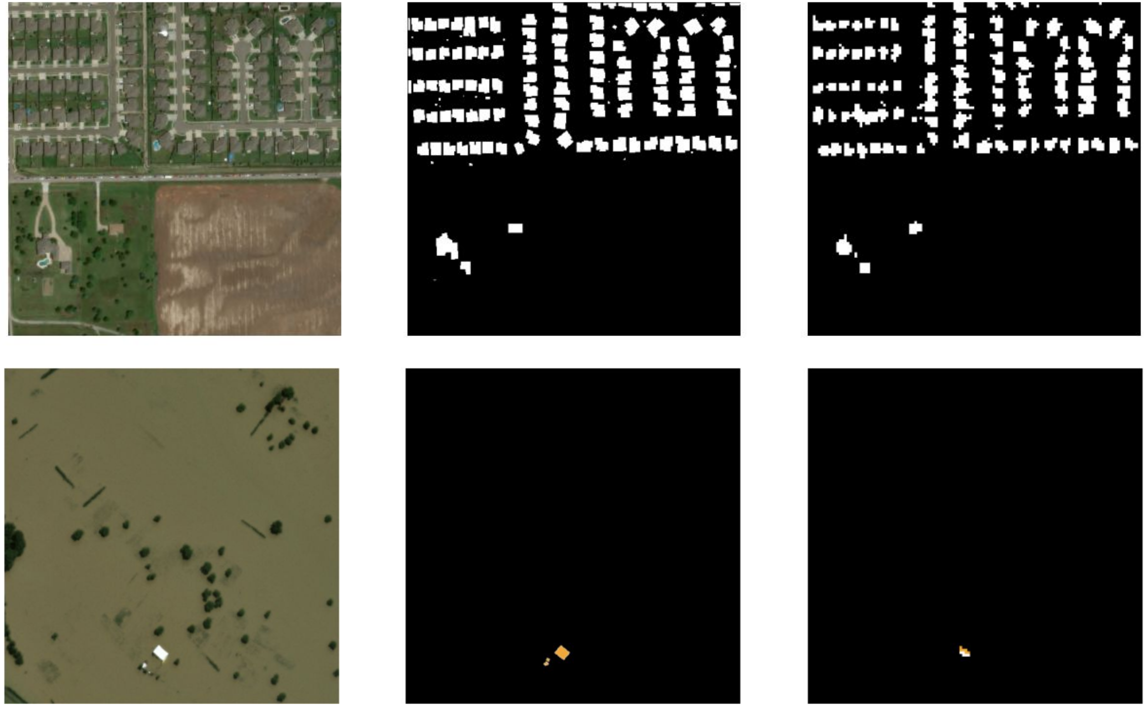
Class	F1 score - Puna Volcano
No building	0.99
No damage	0.43
Minor damage	0.00
Major damage	0.00
Destroyed	0.03

Model 1 Results

Post- disaster image | True mask | Prediction of Model 1

Moore - Tornado

Nepal - Flooding



no building or no classification

no damage

major damage

Class	F1 score - Moore Tornado
No building	0.97
No damage	0.79

Class	F1 score - Nepal Flooding
No building	0.99
Major damage	0.46

Training Scheme of xView2 Model (Model 2)

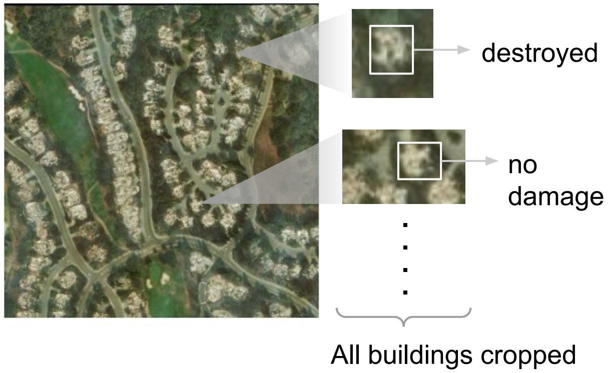
Pre-disaster images* &
Building labeling

Step 1: localization

Training a pre-trained Deep Learning **Semantic Segmentation** Model (UNet)

Post-disaster images* &
Damage label

Step 2: classification



Training a pre-trained Deep Learning **Object Detection** Model (ResNet50)

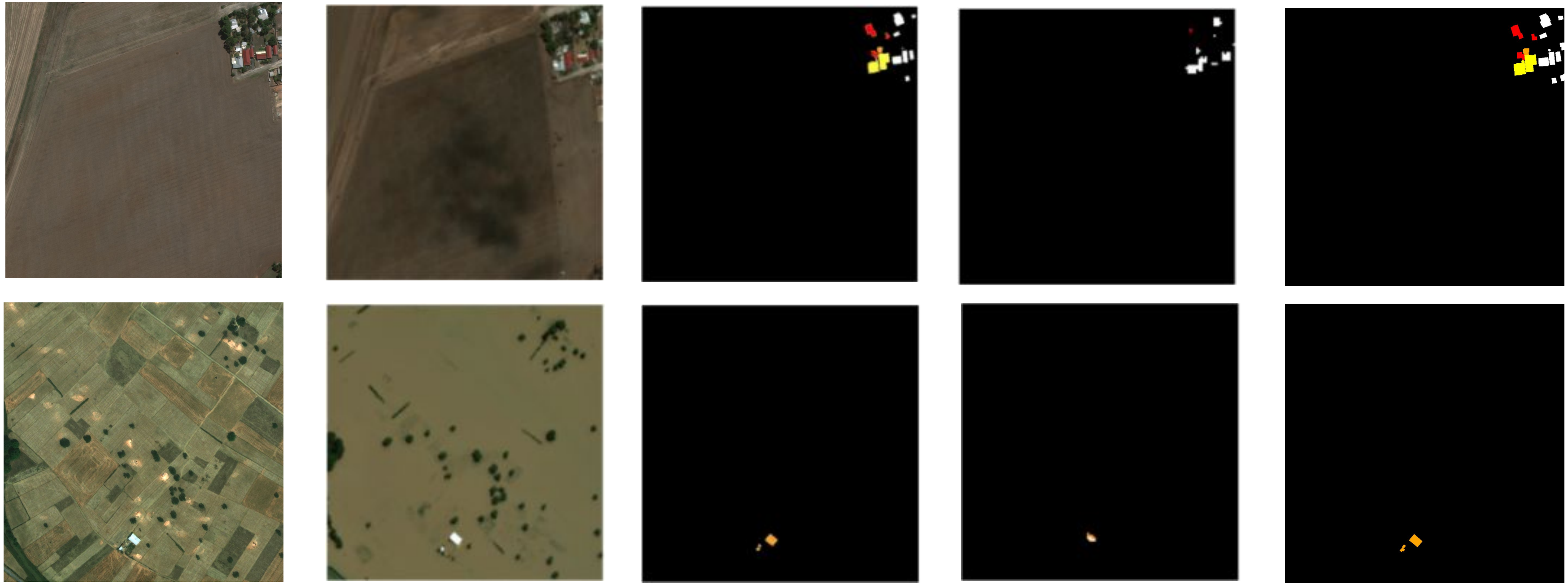
**Santa Rosa - Wildfire*

Model 2 Results

Pre-disaster image | Post-disaster image | True Mask | Prediction - Model 1 | Prediction - Model 2

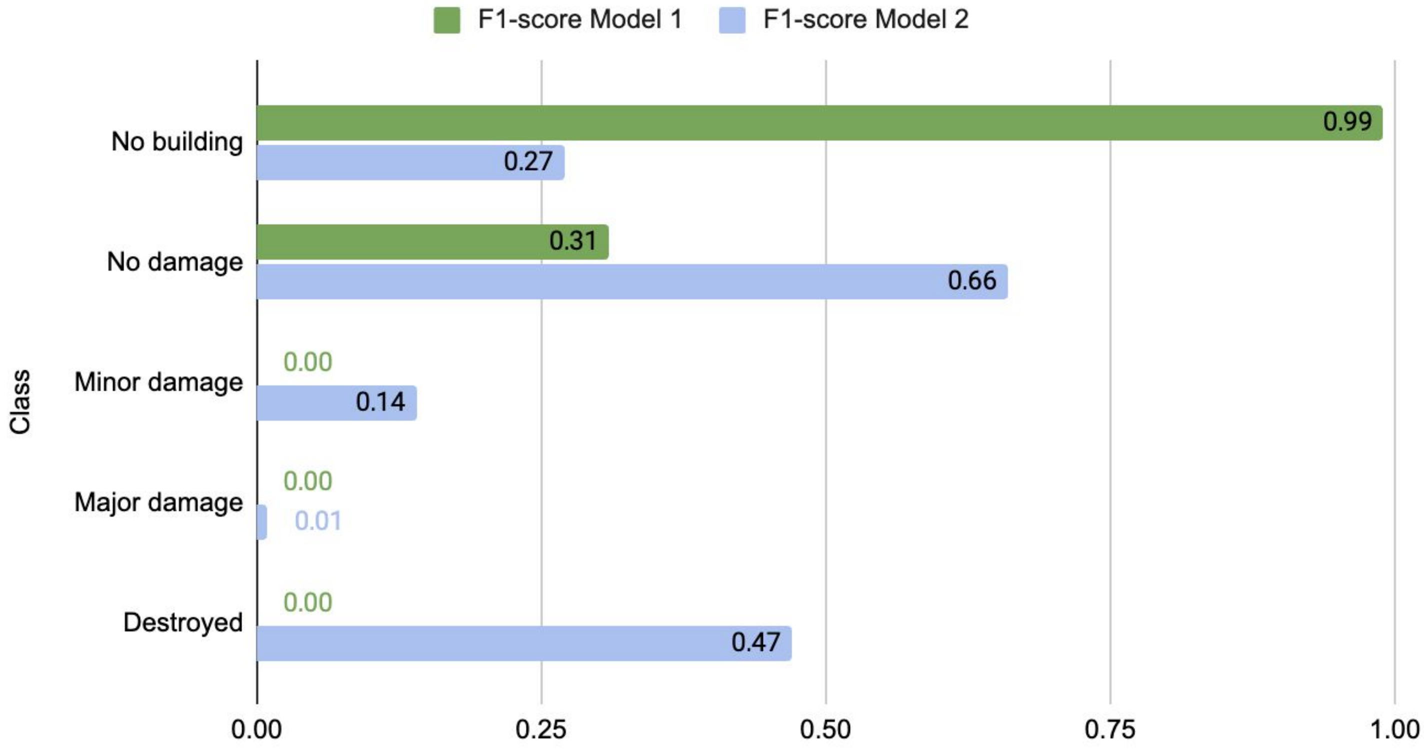
Pinery -Bushfire

Nepal - Flooding



no building or no classification | no damage | minor damage | major damage | destroyed

Performance of Models 1 & 2



Summary

Model 1 (SegFormer model):

- is better at detecting buildings rather than assessing damage level, depending on the disaster

- can be used for damage assessment after natural disasters with further improvement.

Model 2 (xView2 two-step model) performs better than Model 1 since:

- Trained on more images (2800 image pairs in Model 2 vs.1353 image pairs in Model 1)
- More training iterations (100 iterations in Model 2 vs.10 iteration in Model 1)

None of the models compare the image of a building before and after the disaster to determine class label, but uses mainly the post- disaster images for damage assessment.

Discussion and Future Directions

Model 1 can be further improved.

Potential areas of improvement:

- Implement a shared feature extraction module that receives pre- and post-images as input
- Increase the number of images to train
- Address the problem of highly imbalance damage categories (augmentation- flipping, rotating, etc)
- Increase training iterations to increase accuracy of predictions

Thanks for your attention

Questions??