DisasterNet: Automatic Disaster Detection from Aerial Imagery

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Goal: Efficiently Find Badly Hit Areas After Disasters

- First responders rely on disaster area windshield surveys and manual satellite image inspection, which is time consuming, error-prone, and oftentimes physically challenging.
- We train a Convolutional Neural Network (CNN) framework to identify areas hit by disasters.
- Emergency managers could run model in minutes and use results to prioritize rescue and resource allocation.

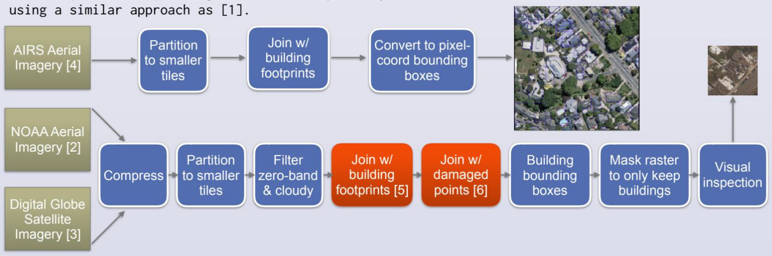
Framework Input & Output

Input: Post-disaster satellite and flight/aerial images covering large areas (RGB images)
Output: Vector with damaged or not-damaged label for individual buildings detected in the original imagery (1D vector)

- Damage labels can be joined back to the building's coordinates, to finally return a vector of locations where damage was detected by the framework.
- We apply this to Hurricane Maria, which damaged or destroyed more than one third of the homes in Puerto Rico.

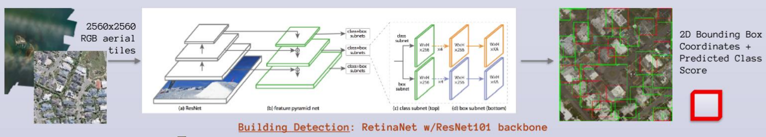
Training Data

- **Buildings in photographs of the Earth are unlabeled!** Bonus: original imagery is too large to process at once (~35,000x35,000px).
- Images can be cloudy, blurry, or include empty-band (black) sections on the edges that can throw the models off.
- No single source for all the data we need: aerial imagery, building footprints, and ground truth for damaged buildings. **We gathered them separately and combined it all to create our datasets**, using a similar approach as [1].

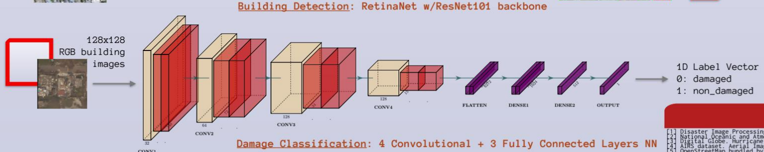


Framework Architecture

- Framework consists of two CNNs: one for **building detection**[7] and another for **damaged building classification**[8].



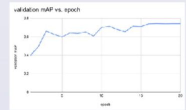
Building Detection: RetinaNet w/ResNet101 backbone

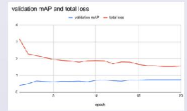


Damage Classification: 4 Convolutional + 3 Fully Connected Layers NN

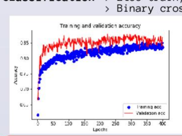
Results

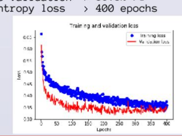
Building Detection
- › Adam, 0.0001 learn rate
- › 15216 train, 2000 validation
- › Focal loss function
- › **0.743 mAP** (validation)
- › 0.25 IoU thresh
- › 20 epochs





Damage Classification
- › Adam, 0.001 learn rate
- › Dropout, 0.5
- › 2406 train, 428 validation
- › Binary cross entropy loss
- › **384 test samples**
- › **84.1% acc**
- › **86.8% F1**
- › 400 epochs





Hyperparameter Tuning

< Building Detection

Learn Rate	Loss
0.001	2.35 (no convergence)
0.0001	1.5685
0.00001	1.9322
0.000001	2.2 (too slow)

Loss	ResNet101	ResNet50
Total	1.5277	1.6626
Reg.	1.2484	1.3483
Class.	0.2793	0.3143

Damage Classification >

Data Aug	Dropout	Building box zoom	# FC Layers	# Frozen Conv Layers	# Epochs	Accuracy
No	0.5	0.00016	2	4	100	53.9%
Yes	0.5	0.00016	2	4	100	52.7%
Yes	0.5 (2 FC)	0.00024	3	2	100	83.9%
Yes	0.5 (2 FC)	0.00024	3	3	100	83.3%
Yes	0.5 (2 FC)	0.00024	3	3	400	84.1%
B	A	S	E			61.4%

Discussion

- Combining two CNN models for two tasks to ultimately perform one objective works! However, performance would likely have been better with more training data. Raw satellite imagery requires a non-trivial amount of preprocessing and visual inspection.
- We chose Hurricane Maria to test current literature performance on a different environment (climate and infrastructure) than those previously evaluated (mainland US). Damage classification base model performance was poor in spite of similarity of the task; however, transfer learning on images from new environment proved effective. A greater diversity of disaster types and environments would make the model more robust.
- This deep learning technique can have a big impact in helping first responders identify first-pass, worst-hit areas immediately following a disaster.

Future Work

- Labeling more aerial/satellite post-disaster images, for Hurricane Maria and other disasters, would likely increase performance and make the framework more robust.
- With more data, we could also explore an end-to-end model that can detect damaged buildings without a two-model framework with separate tasks.

References

[1] Disaster Image Processing. Utils for satellite image processing. https://github.com/DDS-Lab/disaster-image-processing.
[2] National Oceanic and Atmospheric Administration. Hurricane Maria aerial imagery. https://storms.ngs.noaa.gov/storms/maria/index.html.
[3] Digital Globe. Hurricane Maria satellite images. https://www.digitalglobe.com/opendata/hurricane-maria/post-event.
[4] AIRS dataset. Aerial Imagery for Roof Segmentation. https://www.airs-dataset.com/.
[5] OpenStreetMap bundled by GeoFabrik. Puerto Rico building footprints. http://download.geofabrik.de/.
[6] FEMA. Hurricane Maria damage assessments. https://data.femadata.com/NationalDisasters/HurricaneMaria/.
[7] Tsung-Yi Lin, Priyal Goyal, Ross Girshick, Kaiming He, and Piotr Dollar. Focal loss for dense object detection. IEEE Transactions on Pattern Analysis and Machine Intelligence, PP:1-1, 07 2018.
[8] Cao and Choe. Deep Learning based damage detection on post-hurricane satellite imagery. CoRR, abs/1807.01688, 2018.