Detecting Damaged Buildings based on Post-Hurricane Satellite Imagery

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Springboard Capstone Project

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Context

- In 2017 Hurricane Harvey was a caused catastrophic flooding and many deaths to the Greater Houston area.
- The resulting floods inundated hundreds of thousands of homes, which displaced more than 30,000 people and prompted more than 17,000 rescues.

Problem

- After a hurricane, damage assessment is essential to emergency workers and first responders so resources can be planned and designated accordingly.
- One way to gauge the damage extent is to detect and quantify the number of damaged buildings, which is typically done by ground survey methods.
- The goal of this study is to improve the efficiency and accuracy of building damage detection with image classification algorithms.

Who Might Care?

First responders & emergency workers

Politicians

The Data

- Satellite images from Texas after Hurricane Harvey divided into two groups (damage and no_damage).
- **train:** 5000 images of each class
- **validation:** the validation data; 1000 images of each class
- **test unbalanced:** 8000/1000 images of damaged/undamaged classes
- **test balanced:** 1000 images of each class
- All images are in JPEG format. The dataset is available for download via the following link: https://www.kaggle.com/kmader/satellite-images-of-hurricane-damage

Data Wrangling

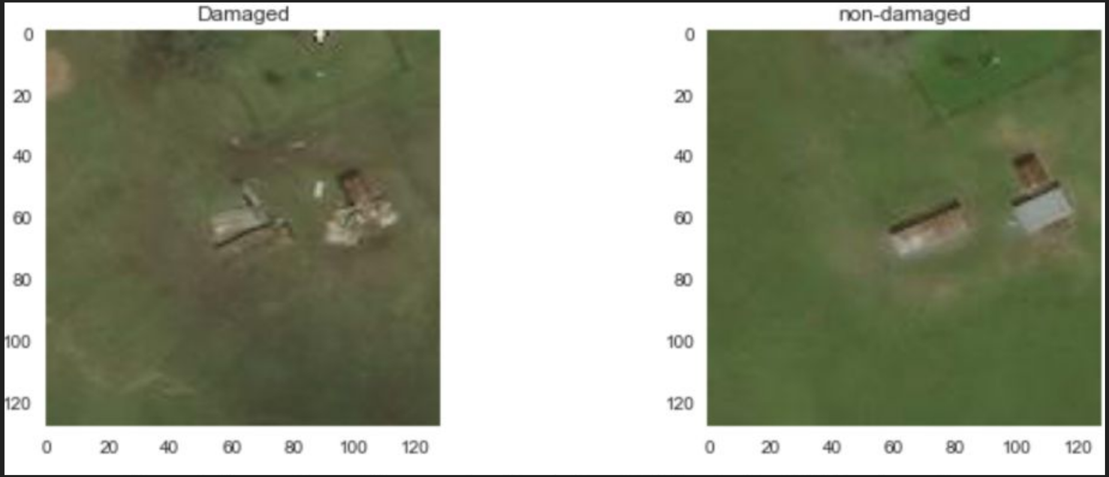
	path	damage	data_split	location	lon	lat	image
0	C:\Users\Jake Wojcik\Documents\Springboard\DS ...	damage	test	-93.548123_30.900623	-93.548123	30.900623	[[[27, 37, 26], [26, 36, 25], [25, 35, 24], [2...
1	C:\Users\Jake Wojcik\Documents\Springboard\DS ...	damage	test	-93.560128_30.894917	-93.560128	30.894917	[[[39, 62, 44], [37, 60, 42], [32, 55, 37], [2...
2	C:\Users\Jake Wojcik\Documents\Springboard\DS ...	damage	test	-93.578271_30.779923999999998	-93.578271	30.779924	[[[102, 105, 74], [102, 105, 74], [100, 103, 7...
3	C:\Users\Jake Wojcik\Documents\Springboard\DS ...	damage	test	-93.590598_30.694956	-93.590598	30.694956	[[[87, 96, 77], [89, 98, 79], [76, 85, 66], [4...
4	C:\Users\Jake Wojcik\Documents\Springboard\DS ...	damage	test	-93.604017_30.793719	-93.604017	30.793719	[[[83, 88, 48], [84, 89, 49], [86, 91, 51], [8...

Steps taken to clean data:

1. Pathlib library in order to extract relevant features of the images into a dataframe.
2. Columns: file path, damage, data_split, location, longitude, latitude, and image in matrix format.

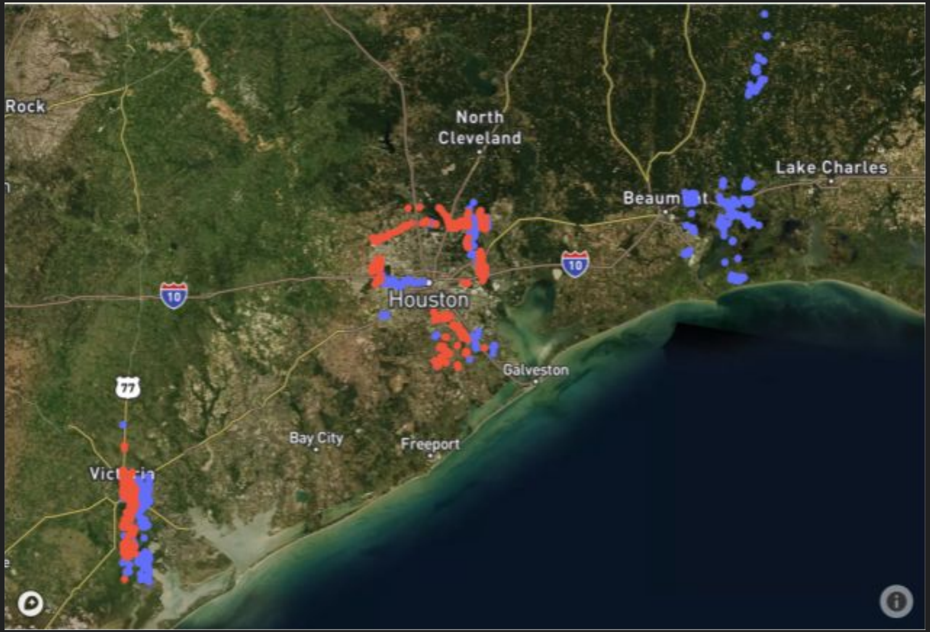
Dealing with Duplicates

- Out of the 12,000 train and validation images, 9476 unique locations in which the images were taken.
- Several images taken at the same location but one before the hurricane (undamaged) and one after the hurricane (damaged).



Exploratory Data Analysis: Location

- Each image overlaid on a map of the greater Houston area labelled by damaged and undamaged.
- Most of the damaged buildings occur on the banks of rivers and waterways.



Color Distribution

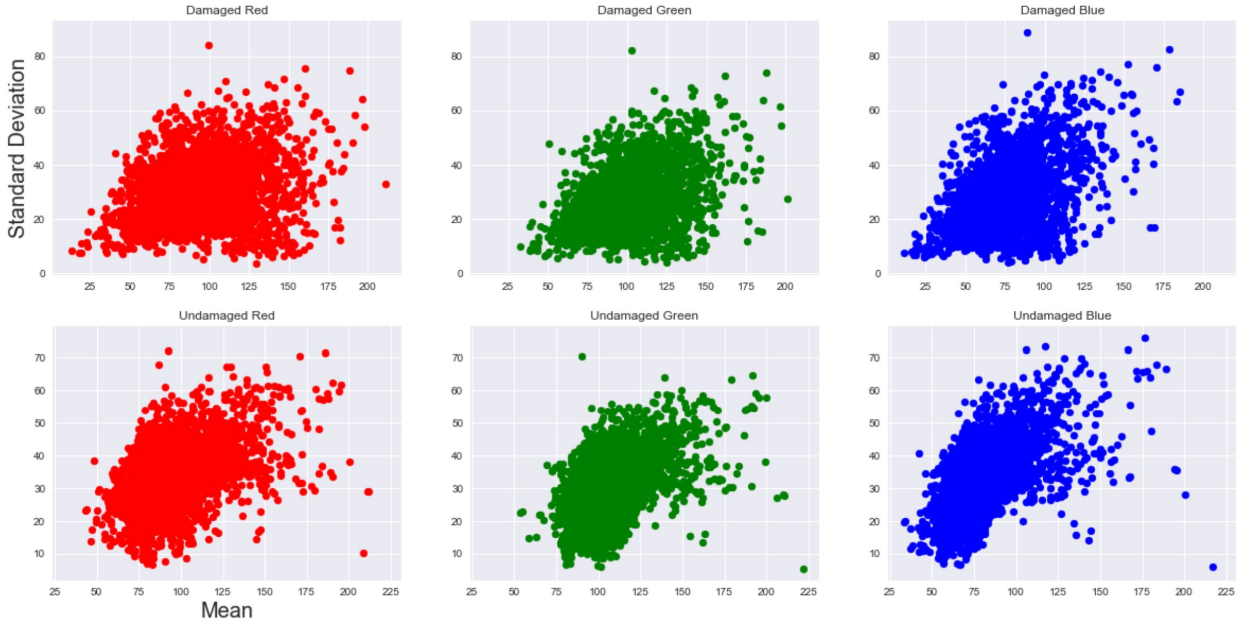
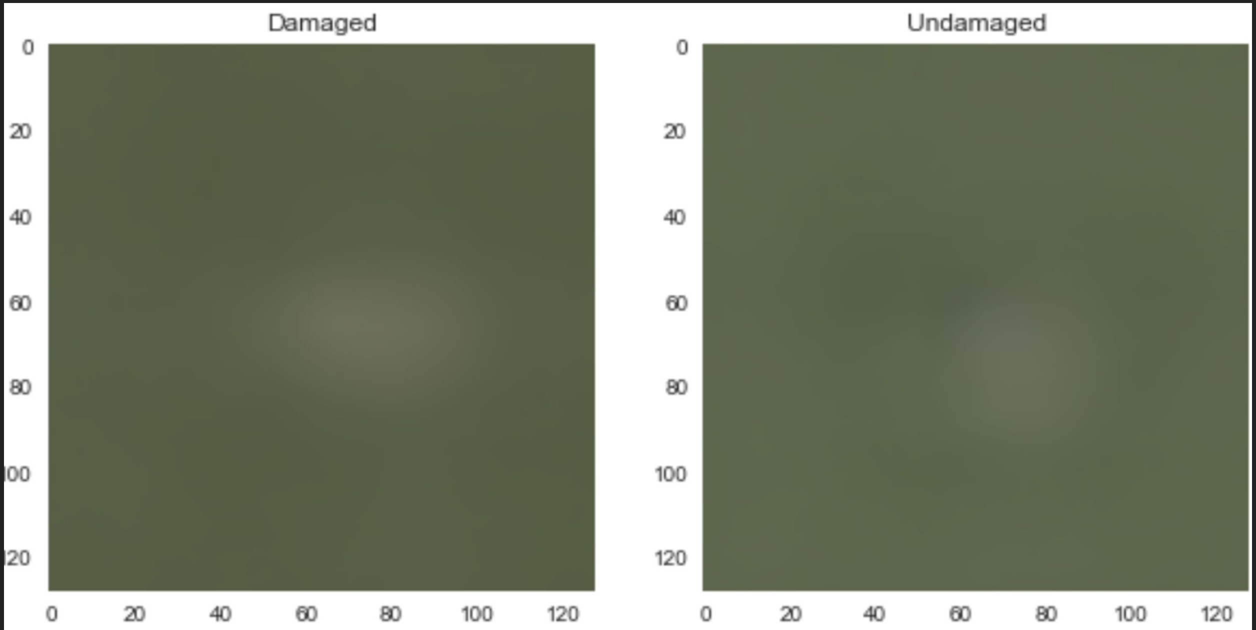


Figure 4: Standard deviation vs. mean in all three color channels. Damaged images are on the top and undamaged images are on the bottom.

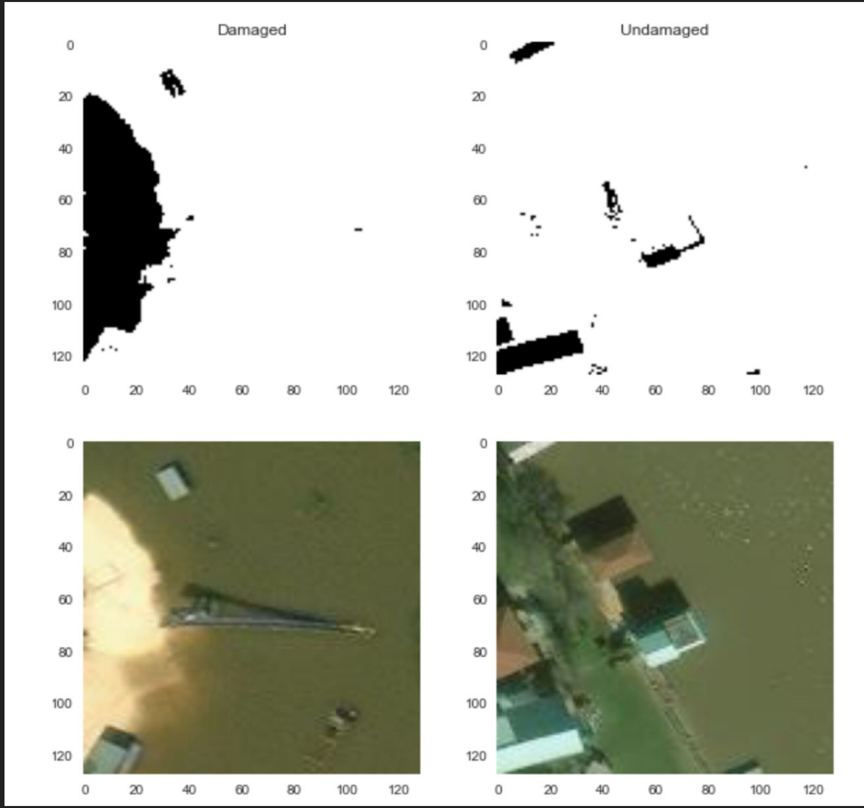
- Undamaged images have more outliers,
- Damaged images have more variance overall than the more tightly clustered undamaged images.
- Undamaged images have more color intensity in all three channels by taking the mean value in each channel

Mean Image & Structural SImilarity Index

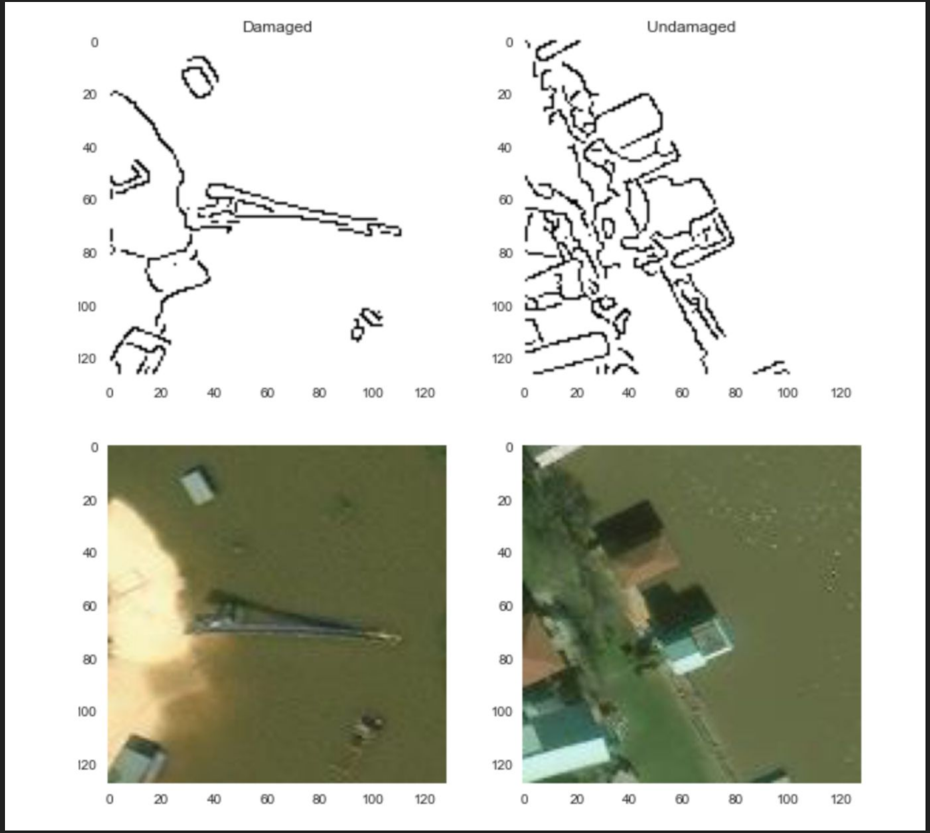


- SSIM score of 0.98
- Damaged images appear to have a slightly more green tint than the non-damaged images.

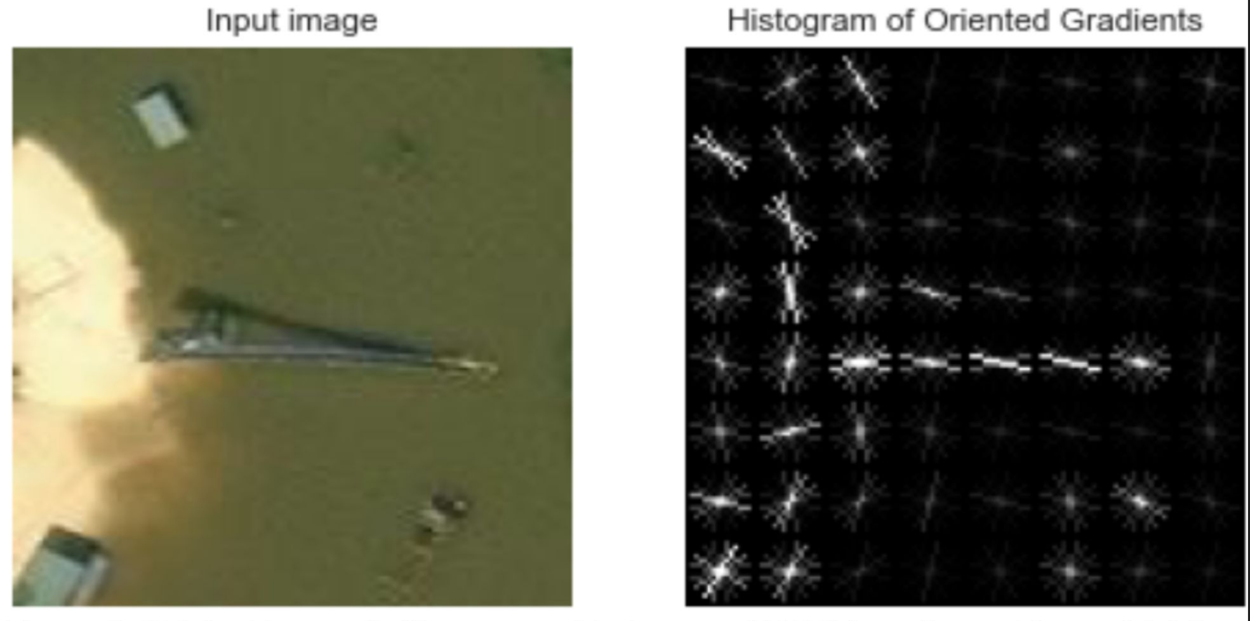
Object Detection: Thresholding



Object Detection: Canny Edge Detector



Object Detection: Histogram of Oriented Gradients



Modeling

1. 32 filters that form a stack of 32 feature matrices.
2. Max pooling layer reduces the input feature matrix to half its number of columns and rows.
3. Flattening layer that will transform the matrix into a feature vector.
4. Dropout layer that prevents overfitting.
5. Fully connected layer in which predictions can be made.

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 126, 126, 32)	896
max_pooling2d (MaxPooling2D)	(None, 63, 63, 32)	0
conv2d_1 (Conv2D)	(None, 61, 61, 64)	18496
max_pooling2d_1 (MaxPooling2	(None, 30, 30, 64)	0
conv2d_2 (Conv2D)	(None, 28, 28, 128)	73856
max_pooling2d_2 (MaxPooling2	(None, 14, 14, 128)	0
conv2d_3 (Conv2D)	(None, 12, 12, 128)	147584
max_pooling2d_3 (MaxPooling2	(None, 6, 6, 128)	0
flatten (Flatten)	(None, 4608)	0
dropout (Dropout)	(None, 4608)	0
dense (Dense)	(None, 512)	2359808
dense_1 (Dense)	(None, 1)	513

Total params: 2,601,153
Trainable params: 2,601,153
Non-trainable params: 0

Modeling Performance

Metric	Training	Validation	Balanced Test	Unbalanced Test
Loss	0.04	0.06	0.04	0.04
Accuracy	0.98	0.98	0.99	0.98
F1 Score	0.98	0.98	0.99	0.92
Recall	0.99	0.99	0.98	0.97
Precision	0.98	0.97	0.99	0.89

- The baseline accuracy for the unbalanced test set is 88.89%, which can be achieved by annotating all buildings as the majority class, damaged.
- 98% is a marked improvement.

Model Performance: ROC & Precision-Recall Curves

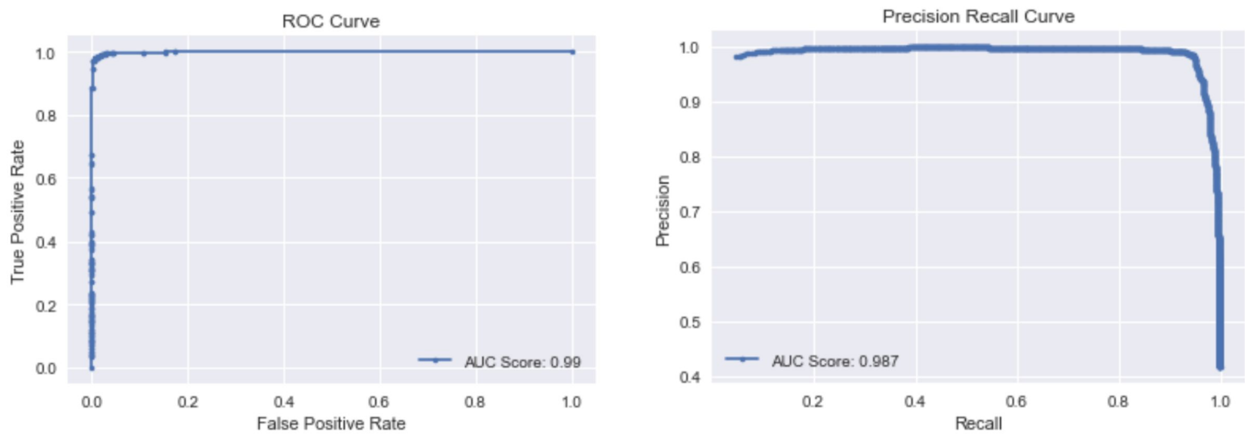


Figure 11: ROC curve (left) & precision-recall curve (right) for our CNN.

- Recall is higher than precision, our model is better at finding members of the positive class than correctly classifying members of the positive class.

Misclassified Images: False Positives

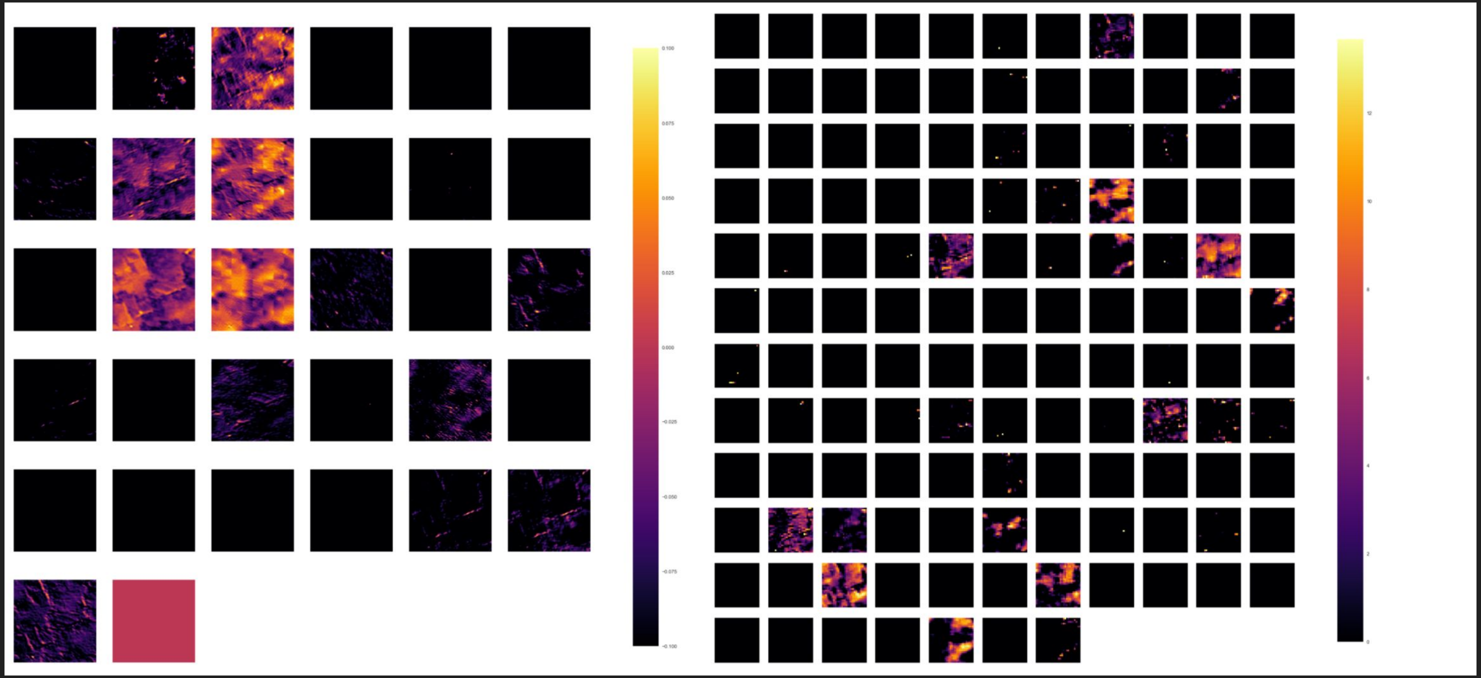
- 1000 possible undamaged images the CNN classified only 27 incorrectly.
- The building in the center of image 16, the water in image 4 and 22, the cloud covering in image 18 and 27 and the parking lot with scattered cars in image 12 can potentially mislead the model.

Misclassified Images: False Negatives

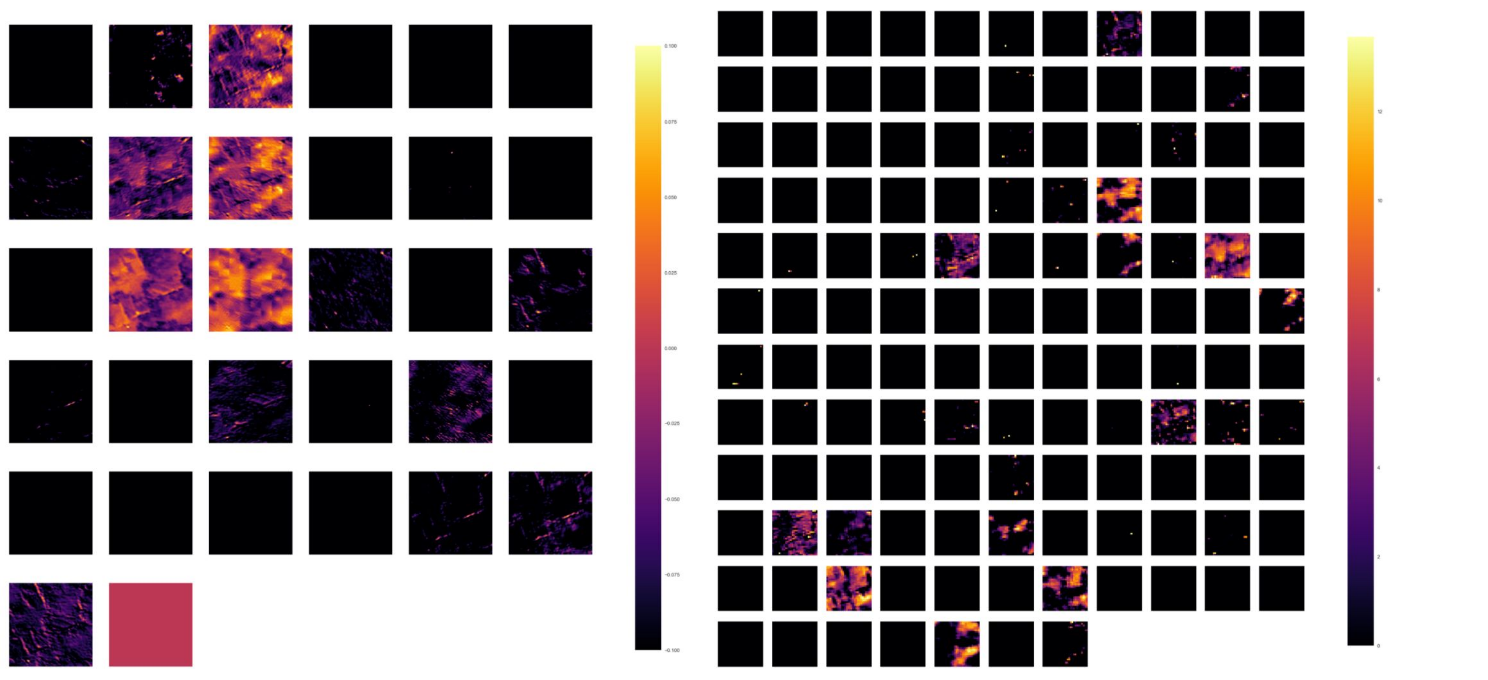
  

- 8000 damaged images the CNN classified only 115 incorrectly.
- Hard to see first image as damaged or flooded.
- Cloud cover might be misleading the model.
- Misclassified the baseball diamond. Could be due to the unique structure.

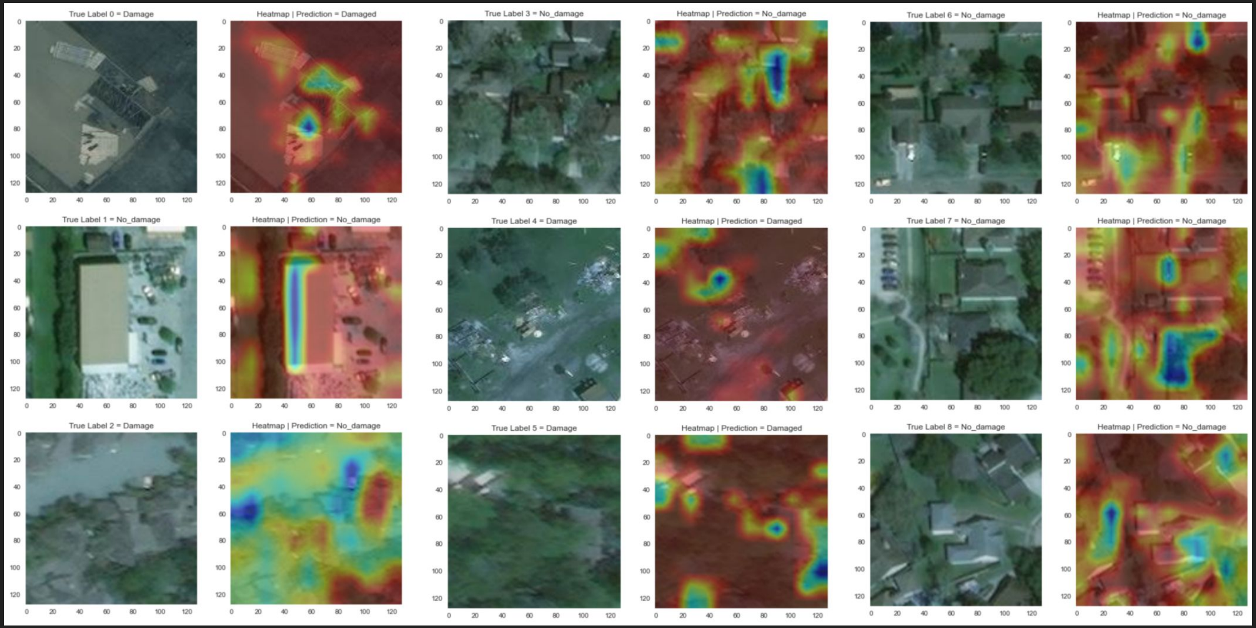
Visualizing Activation Layers: Undamaged



Visualizing Activation Layers: Damaged



Interpreting the Model: Grad-Cam



- Damaged images highlight edges in the form of buildings or debris. Very low gradients surrounding the buildings.
- In contrast, the undamaged images have a more evenly distributed gradient profile across the whole image.

How well does our model generalize to new data?

- 85% classified correctly.
- Need more images for better generalization.

Conclusions & Future Research

- Demonstrated that convolutional neural networks can reliably classify damaged buildings on post-hurricane satellite imagery with high accuracy.
- Model likely uses a combination of features to classify images including: color distribution, mean image & SSIM, and edge detection.
- Model should be able to classify satellite images from lower quality images including images with clouds obscuring part of the land.
- Further investigate how the model could adjust to more noise in the data due to different sizes and zoom levels of each image.
- Extend the model to classify road damage and debris, which could help disaster relief workers plan transportation routes for medical supplies, food, or fuel to hurricane survivors.