Convolutional Neural Nets for Flood Detection

CPSC-393

Introduction

- Annually there is approximately $17 Billion in flood damage
- Over the next three decades the cost of flood damage is on pace to rise of 26%

Current State of the Art Solutions

- Seeking image data
  - Easy to attain
  - Easy to interpret
- Satellite, drone images
- For satellite data
  - U-Net (a type of Fully Convolutional Network)
  - Mask R-CNNs (pixel-wise prediction)

Insurance Uses

Can survey areas determining whether or not there was flood

Humanitarian Uses

Can help direct limited Federal Aid to the area most affected by natural disasters

Data Processing

- *Building Damage Annotation on Post-Hurricane Satellite Imagery Based on Convolutional Neural Networks* (Cao and Choe, 2020)
- Satellite images of Houston, TX buildings
- Damaged (data from volunteers) and undamaged
- One building per image
- Removed any images with
  - Clouds
  - Blacked-out portions

Data Info

- 10,000 training images around size 128x128
  - 5,000 damage
  - 5,000 no damage
- 2,000 validation images
  - 1,000 damage
  - 1,000 no damage
- 2,000 test images
  - 1,000 damage
  - 1,000 no damage

Our Model

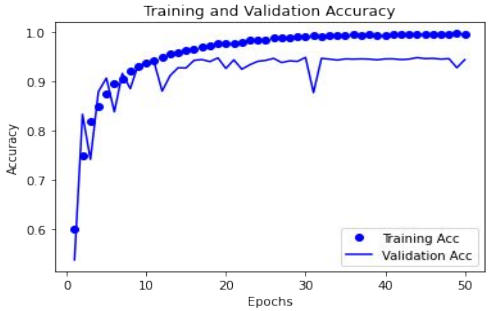
Our Models

Convolutional Neural Net Model

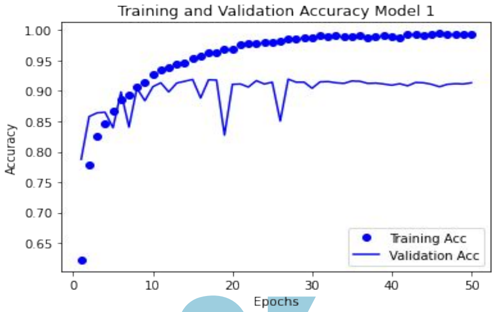
- Final Relu Sigmoid Activation
- Binary_Cross Entropy - Loss
- ACC - Metric

Models

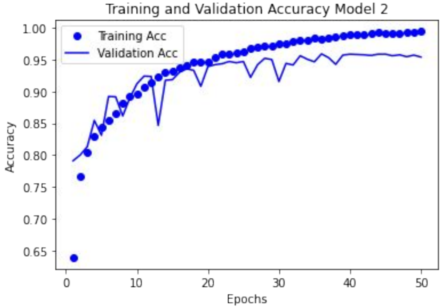
00
1 Conv + Pool Layer



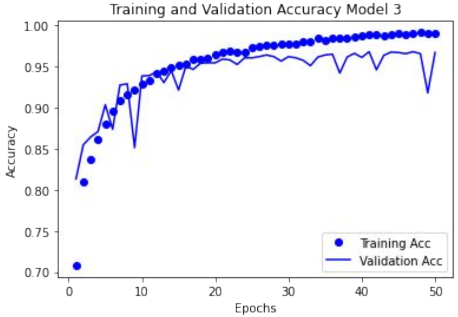
01
5x5 Window



02
5 Hidden Layers

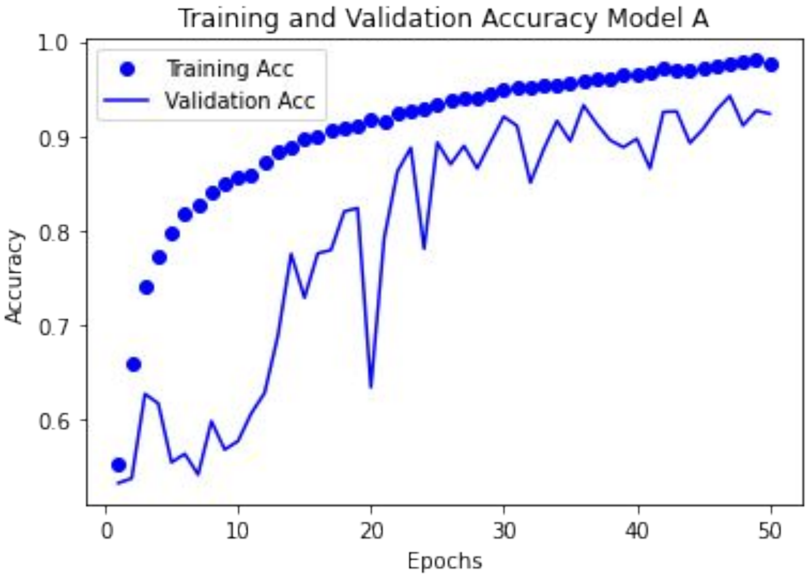


03
7 Hidden Layers

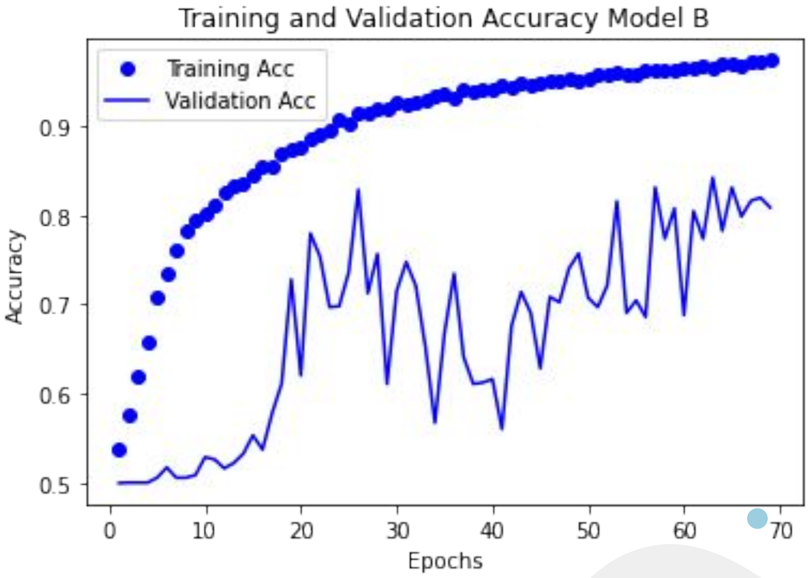


Model A and Model B

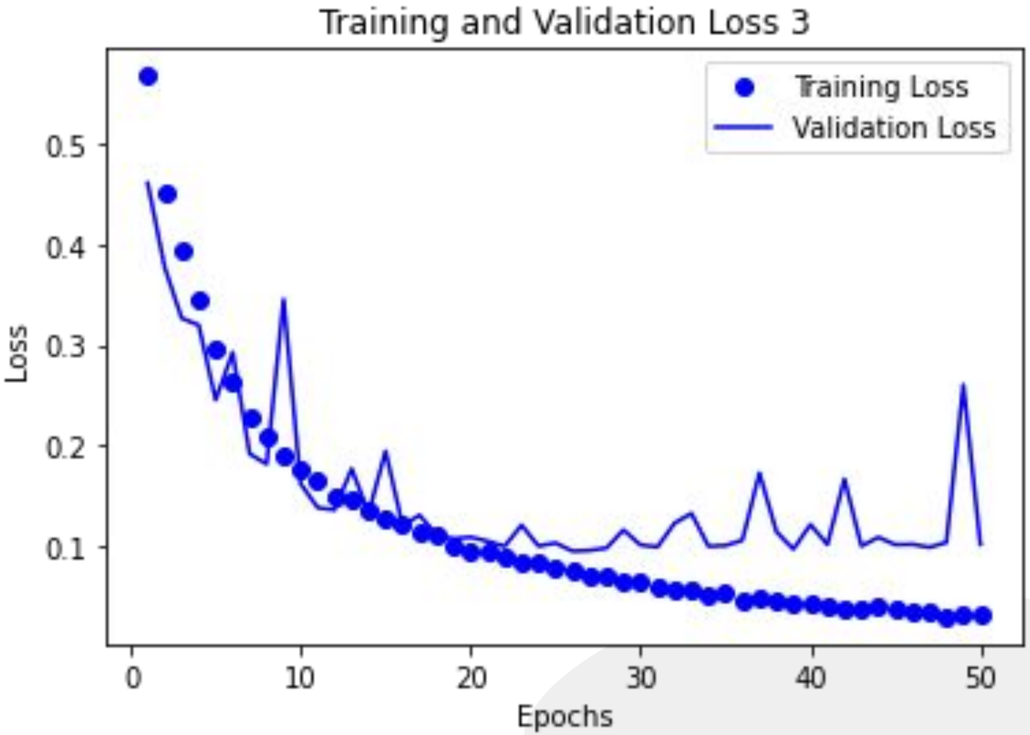
0.25 Dropout



0.50 Dropout



Model 3



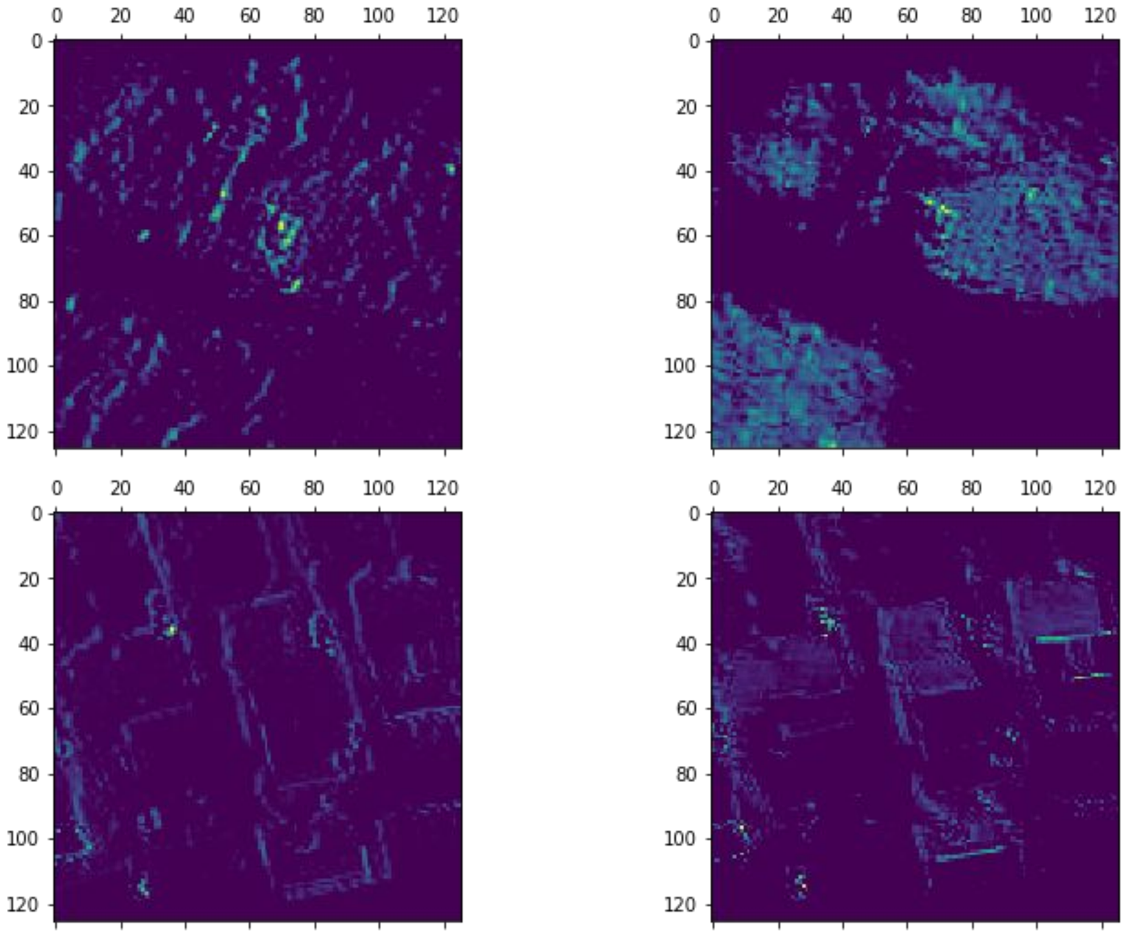
Testing Loss: 0.067

Training Loss: 0.032

Testing Accuracy

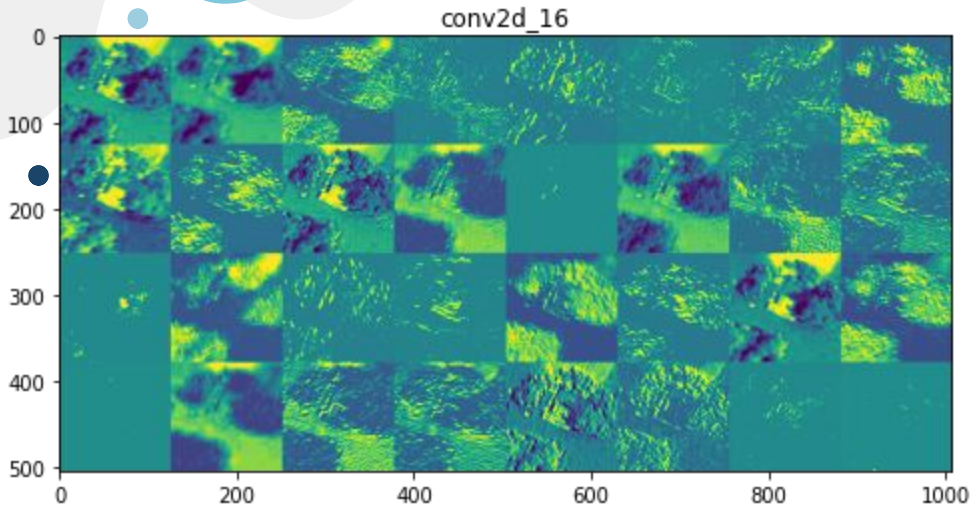
98.0%

Visualizing the Model



Damage

Damage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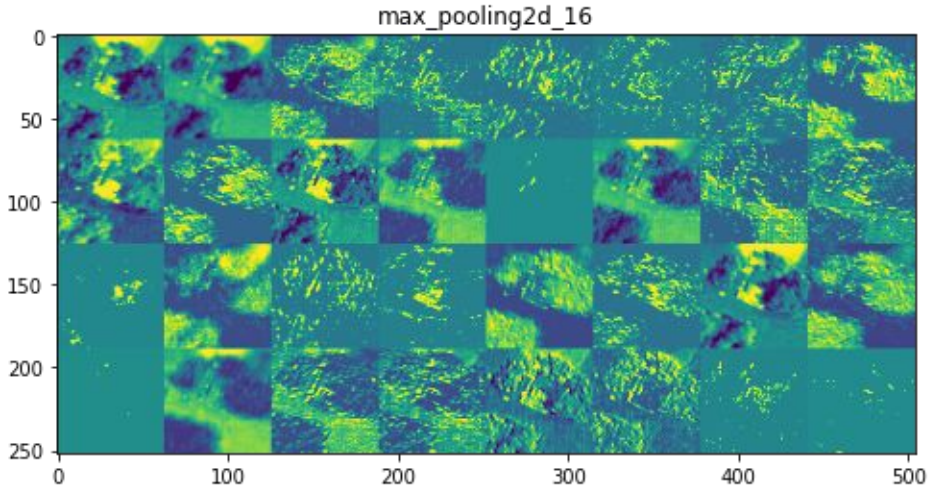
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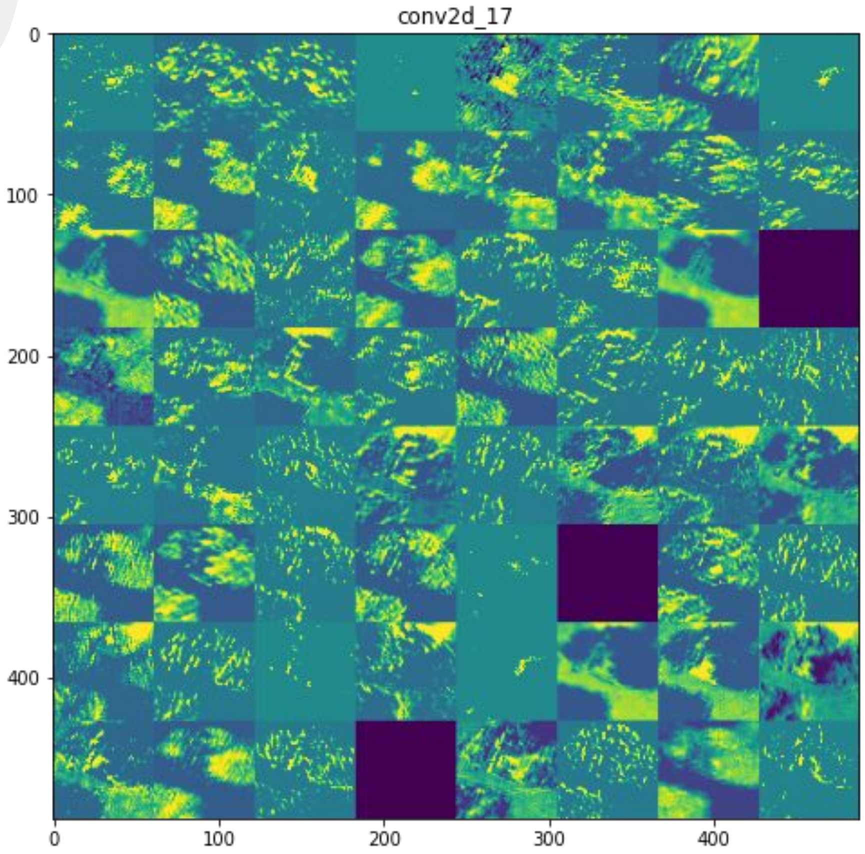
Damage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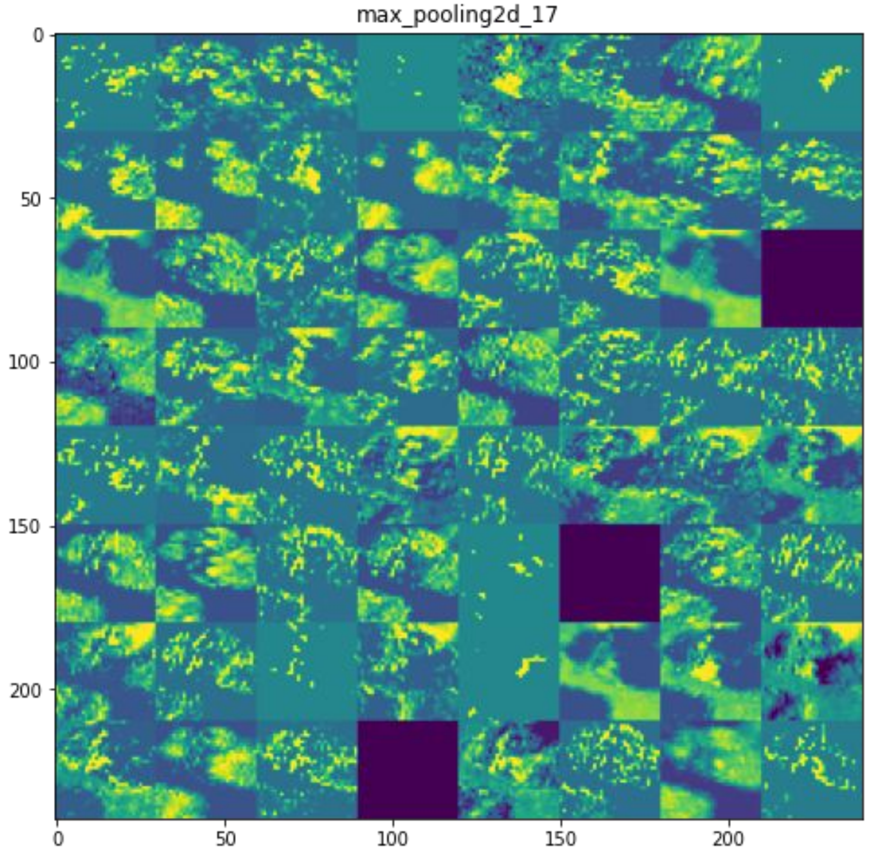
max_pooling2d_17
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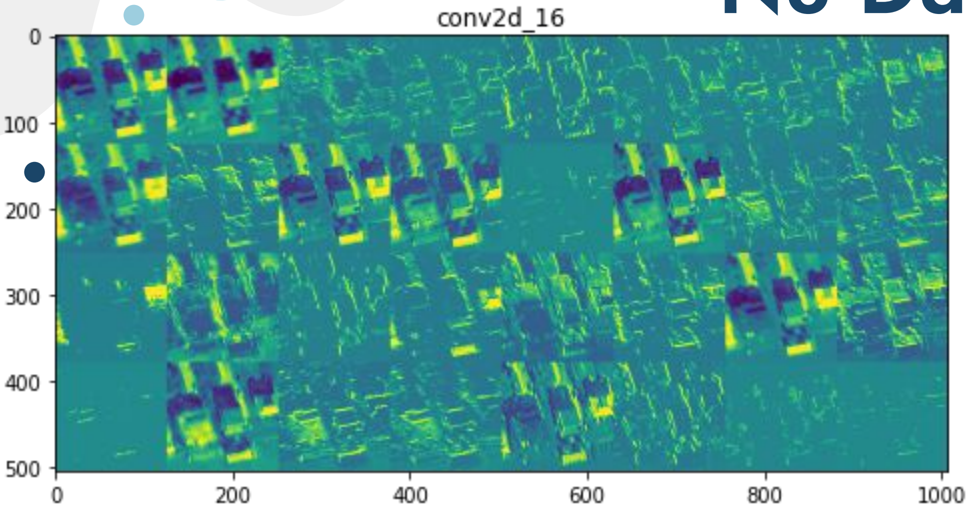
No Damage

No Damage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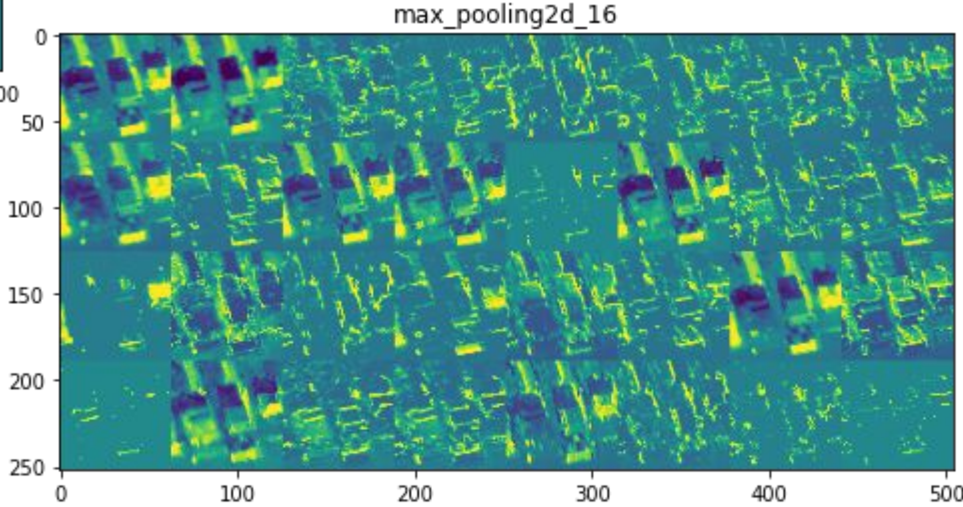
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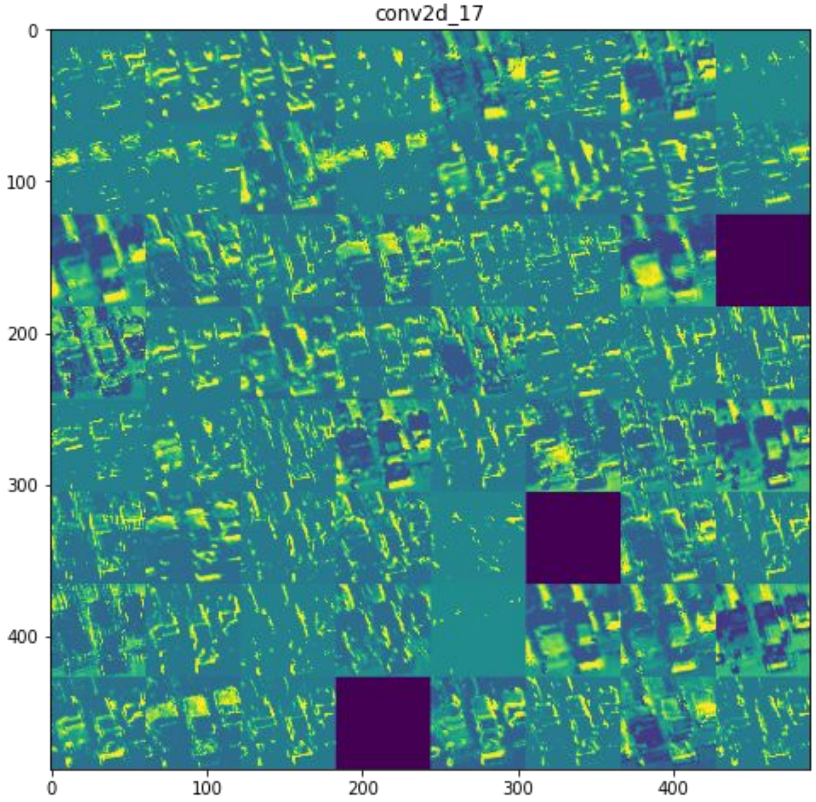
No Damage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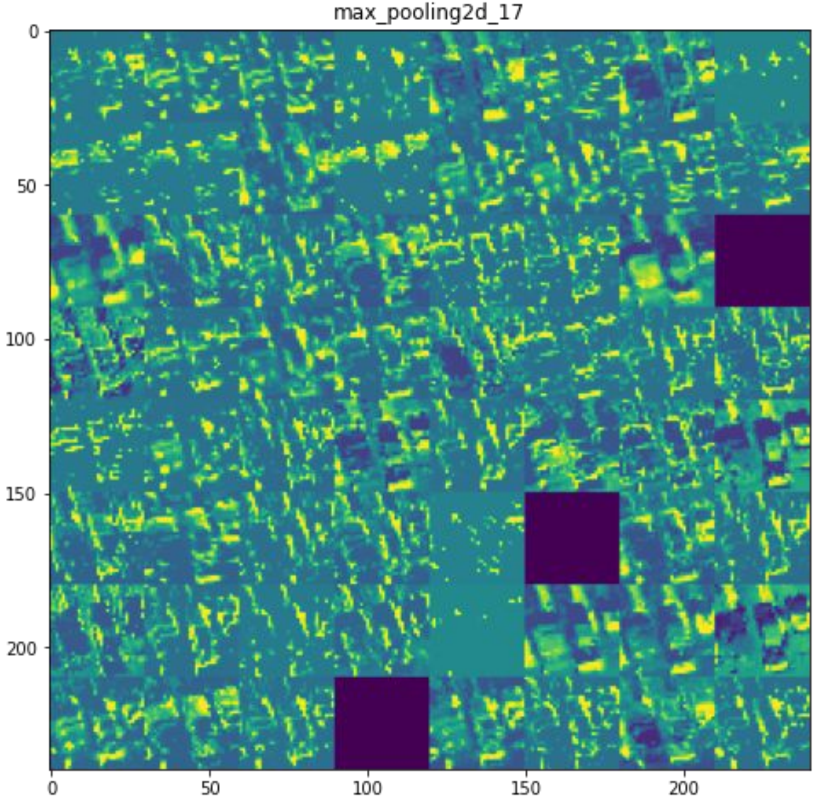
max_pooling2d_17
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Model Architecture

3x3 Convolution Layer

Max Pool

3x3 Convolution Layer

Max Pool

3x3 Convolution Layer

Max Pool

Flatten

Relu Dense

Sigmoid

Improving Our Project

- More regularization
- Testing unbalanced data
- Seeking more understanding of feature maps

Real World Applications

Global Implications

Recognizing flood damage around the world

Current Disaster Response

Where current flooding is

Post Disaster Response

Where flooding damage exists

Deployable Uses

Real time detection of flooding and damage

Our Model in the Real World

- Currently trained on Houston satellite images
- Other climates/terrains are susceptible to flooding
- This model recognizes Houston buildings and terrain
- Other terrain and architecture?

Application Problems

- Time to gather data
- Appropriately cleaning data
- Obtaining consistent data
    - Satellite, drone, etc.

Sources

- https://www.scientificamerican.com/article/new-maps-show-us-flood-damage-rising-26-percent-in-next-30-years/
- https://www.bbc.com/news/av/world-europe-61325769
- https://www.reuters.com/world/asia-pacific/half-million-face-flood-evacuation-sydney-braces-more-heavy-rains-2022-03-02/
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- https://www.frontiersin.org/articles/10.3389/frai.2020.534696/full

Thanks

Do you have any questions?
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