Extreme event monitoring using the remote sensing of infrastructure as a key parameter
Background
Natural Disasters
- 60,000 Deaths a Year
- Immense infrastructure damage and economic loss
- Increasing in frequency and intensity due to climate change

Satellite Imagery
- Quick and efficient, aids in the allocation of resources
- Analyzed with deep learning based approaches to classify building damage
Previous Works

- **Image Classification**
  - Classical approaches, deep-learning techniques

- **Computer Vision for Satellite Imagery**
  - Marine ecology, weather forecasting, spread of disease
  - Agriculture, urban road damage
  - Change detection (multi-temporal fusion)
Previous Works

- Building Damage Assessment
  -Semantic building segmentation
  -Cross-region transfer learning
  -Semi-supervised approaches
  -xBD: most comprehensive dataset
- Disaster Relief: Social Media (NLP vs. CV)
- What do we contribute?
  -Interpretability
    -Quantitative and Qualitative
Interpretability

(Def) the degree to which a human can understand the cause of a decision of a machine learning algorithm
Research Process

- Dataset analysis
- Develop a baseline model to classify building damage based on the post-disaster image only
- Develop improvements to the baseline model to classify building damage based on other aspects of the image, namely the pre-disaster image and the disaster type
- Compare the results
- Understand exactly what these networks are learning (leading to more interpretable models)
xBD Dataset

Source: www.xview2.org
Preprocessing

- Creating building crops for per-building analysis, using labeled building polygons provided
- Discarding small/unclear buildings
- Other cleaning mechanisms
- Train on equally distributed dataset (equal number of crops for each category)
Baseline model

- Based on the post-disaster image only
- ResNet18 (CNN architecture) - pre-trained on ImageNet data
- Cross-entropy loss
- Trained on 12,800 building crops
- Adam optimizer
- Learning rate of 0.001
- 100 epochs
- NVIDIA Tesla K80 GPU
Baseline model

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<table>
<thead>
<tr>
<th>Layer Name</th>
<th>Output Size</th>
<th>ResNet-18</th>
</tr>
</thead>
<tbody>
<tr>
<td>conv1</td>
<td>112 x 112 x 64</td>
<td>7 x 7, 64, stride 2</td>
</tr>
<tr>
<td>conv2_x</td>
<td>56 x 56 x 64</td>
<td>3 x 3 max pool, stride 2</td>
</tr>
<tr>
<td>conv3_x</td>
<td>28 x 28 x 128</td>
<td>3 x 3, 128 x 2</td>
</tr>
<tr>
<td>conv4_x</td>
<td>14 x 14 x 256</td>
<td>3 x 3, 256 x 2</td>
</tr>
<tr>
<td>conv5_x</td>
<td>7 x 7 x 512</td>
<td>3 x 3, 512 x 2</td>
</tr>
<tr>
<td>average pool</td>
<td>1 x 1 x 512</td>
<td>7 x 7 average pool</td>
</tr>
<tr>
<td>fully connected</td>
<td>1000</td>
<td>512 x 1000 fully connections</td>
</tr>
<tr>
<td>softmax</td>
<td>1000</td>
<td></td>
</tr>
</tbody>
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Improvements

- New types of input: pre-disaster image and disaster type
- Different loss functions:
  - Ordinal Cross-entropy loss
  - Mean squared error
- Other aspects remain the same
Results: Accuracy comparison

Table 1: Comparison of the Validation Accuracy on 9 Different Models

<table>
<thead>
<tr>
<th>Model Input</th>
<th>Loss Function</th>
<th>Mean Squared Error</th>
<th>Cross-Entropy Loss</th>
<th>Ordinal Cross-Entropy Loss</th>
</tr>
</thead>
<tbody>
<tr>
<td>Post-Disaster Image Only</td>
<td></td>
<td>45.3%</td>
<td>59.5%</td>
<td>64.2%</td>
</tr>
<tr>
<td>Pre-Disaster, Post-Disaster Images</td>
<td></td>
<td>50.2%</td>
<td>68.3%</td>
<td>71.2%</td>
</tr>
<tr>
<td>Pre-Disaster, Post-Disaster Images, Disaster Type</td>
<td></td>
<td>49.7%</td>
<td>72.7%</td>
<td>74.6%</td>
</tr>
</tbody>
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Table 1. Comparison of accuracy on the validation set for nine different models. Unsurprisingly, the models trained on pre-disaster image, post-disaster image, and disaster type (all three modalities) performed the most accurately. Additionally, the models that utilized ordinal cross-entropy loss as their loss function achieved the best results.
Discussion

- Accuracy increases between three models: post-disaster image only, pre-and-post-disaster images, and pre-and-post disaster image plus disaster type.
- Reasons for non-optimal accuracy.
- Ordinal cross-entropy loss is the best criterion.
- Contributes to the study of interpretability in deep learning models that classify building damage.
Figure 1: Gradient class activation maps [20] depict which parts of the building crop lead the baseline model to predict a certain classification. On the top are the original images (crops) and on the bottom are the corresponding gradient class activation maps. The images included are only post-disaster images. From left to right: (1) A building with label “no damage,” after flooding in the Midwestern United States, (2) A building with label “minor damage,” after Hurricane Michael, (3) A building with label “major damage,” after Hurricane Harvey, and (4) A building with label “destroyed,” after Hurricane Michael.
Conclusion

- We find that inputting different combinations of information does indeed improve model performance.
- Our study leads the way for more effective and efficient damage assessment in the event of a disaster.
- Climate change
- AI/ML is key
Future Work

- Other modalities of input
  - Neighboring buildings
- Different combination methods of the pre-disaster image and post-disaster image
- Qualitative interpretability - deployment
- Cleaner dataset, more distinct differences between major damage and minor damage, for instance.
Thanks for listening. Any questions?