Damage Classification Final Presentation

By Alan Cheriyan, Andrew Orlosky, and Pat Marinich

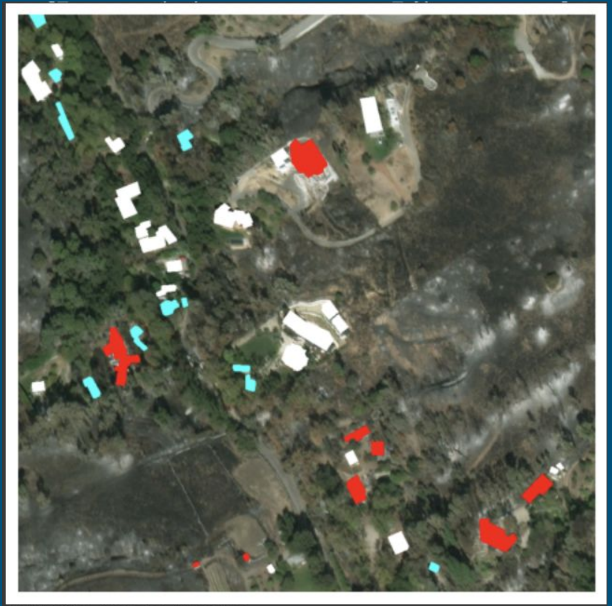
Quick Refresher - Motivation + Objectives

Motivation

- **Big Picture Goal:** Provide the most effective aid post-disaster.
- Capture the **magnitude of damage** in real-time with high accuracy

Objectives

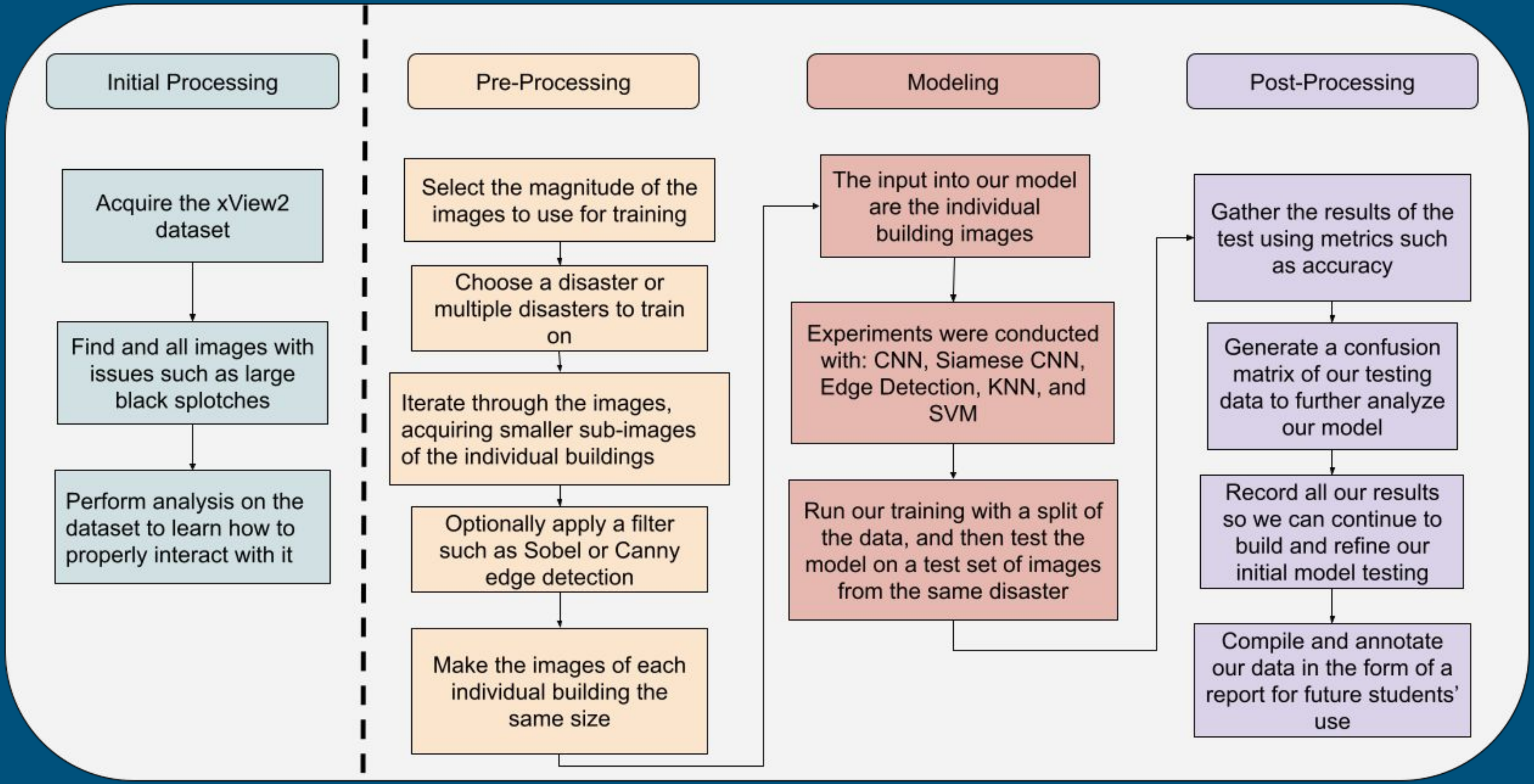
- **Perform Damage Classification**
  - No Damage
  - Minor Damage
  - Major Damage
  - Destroyed
- **Explore Models**
  - Investigate the effectiveness of different models



Building Damage Counts:

	Damage_Type	Count
0	no-damage	21
1	minor-damage	0
2	major-damage	0
3	destroyed	9
4	un-classified	11

Updated Pipeline

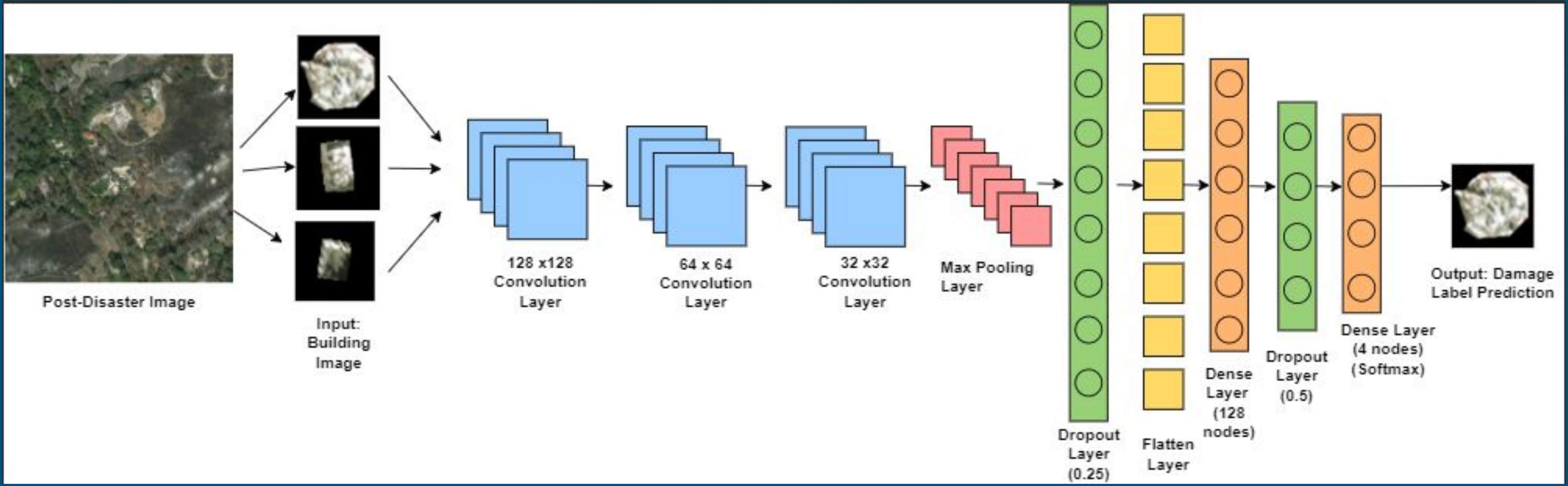


Broad Results - Accuracy

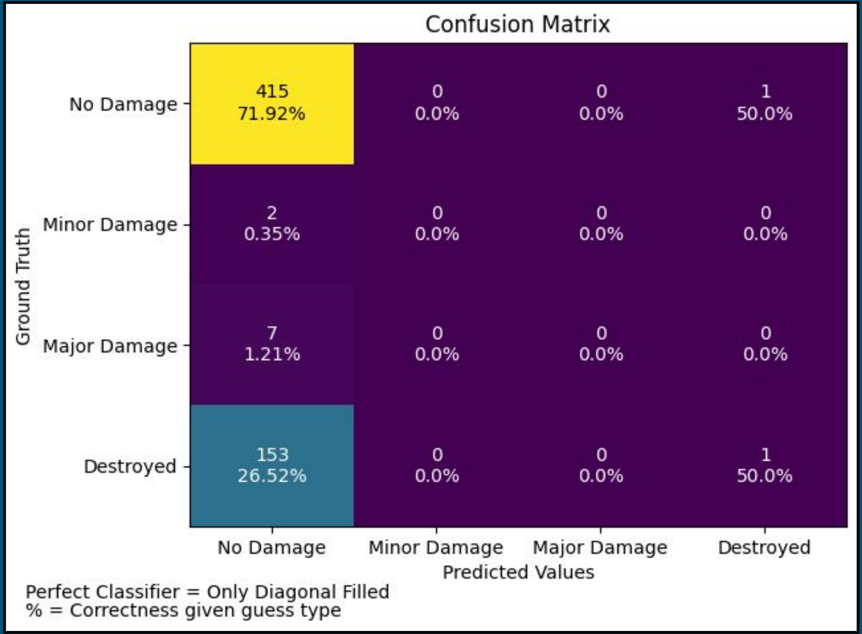
- Disaster type impacted results
- Applying pre-processing filters aided in success
- Skewed categorical data, most data is no-damage
- Traditional Classifiers performed effectively

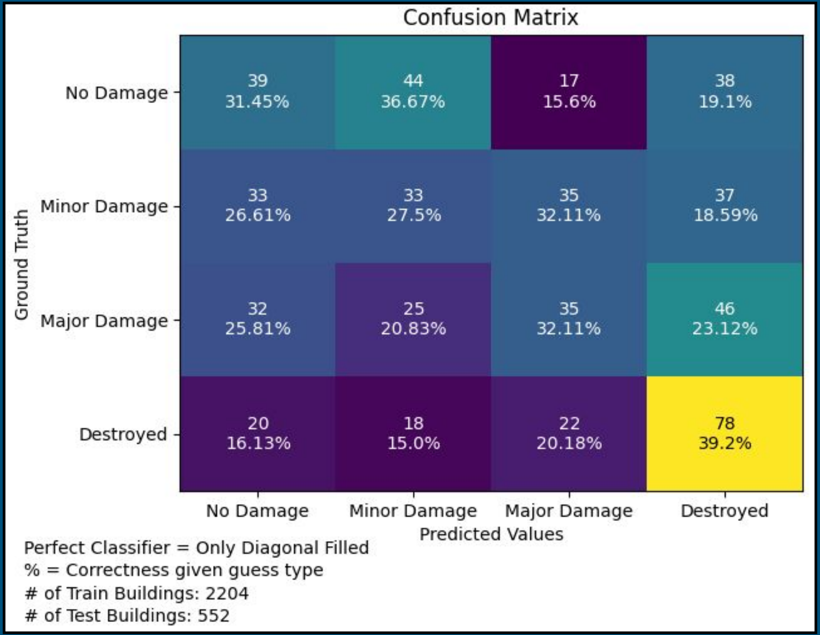
Accuracies	CNN	CNN with Edge Detection	Siamese NN	SVM	KNN Classifier
Hurricane Matthew	55.97%	33.24%	58.30%	54.40%	57.8%
Guatemala Volcano	91.94%	91.79%	32.00%	92.81%	96.89%
Palu Tsunami	83.48%	40.24%	77.5%	62.30%	86.23%
SoCal Fire	84.95%	66.00%	42.33%	82.13%	76.98%

CNN Architecture



CNN - Results and Takeaways





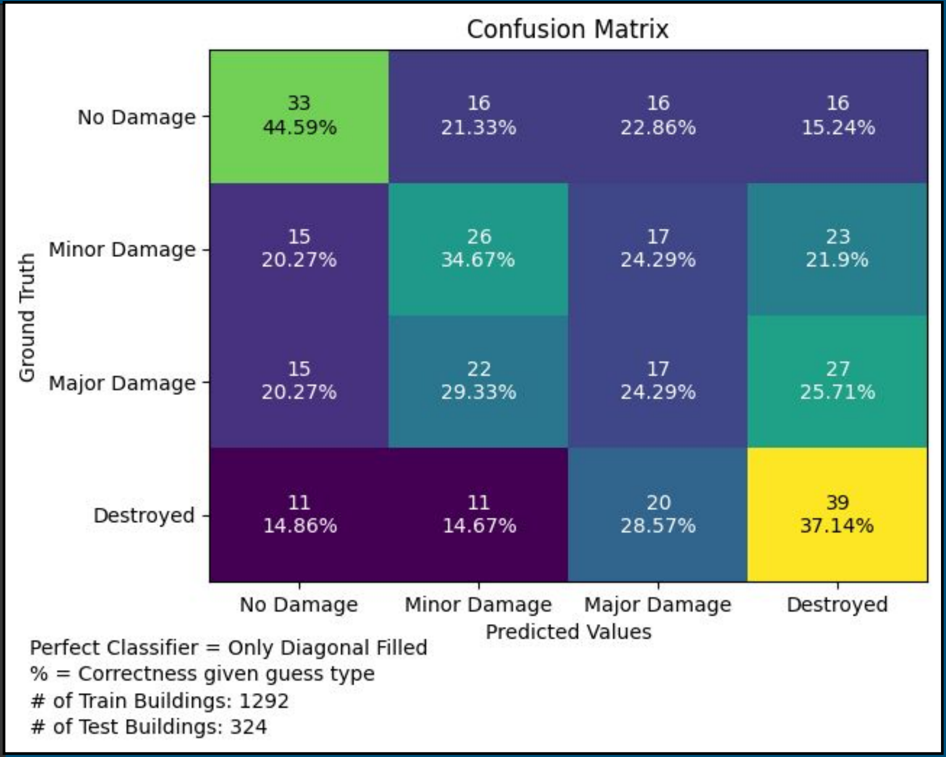
Left: Southern California Fire with larger 7x7 and 5x5 kernel sizes

Right: Hurricane Matthew equal distribution of building damage levels

Although the right model's accuracy is lower, accuracy doesn't always tell the full story

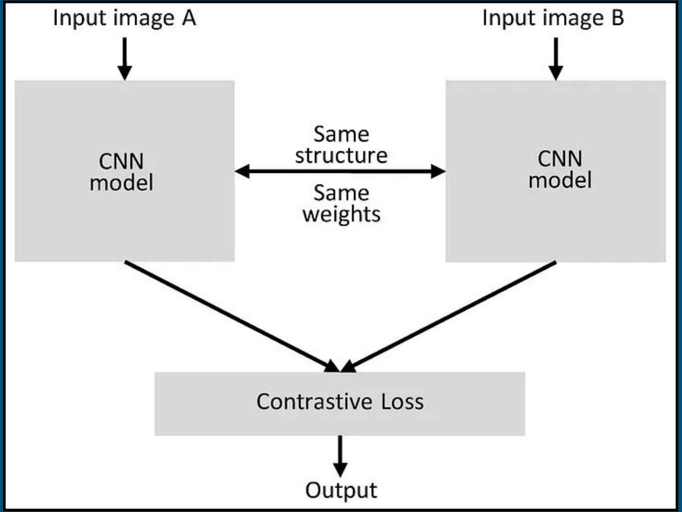
CNN + Edge Detection - Results and Takeaways

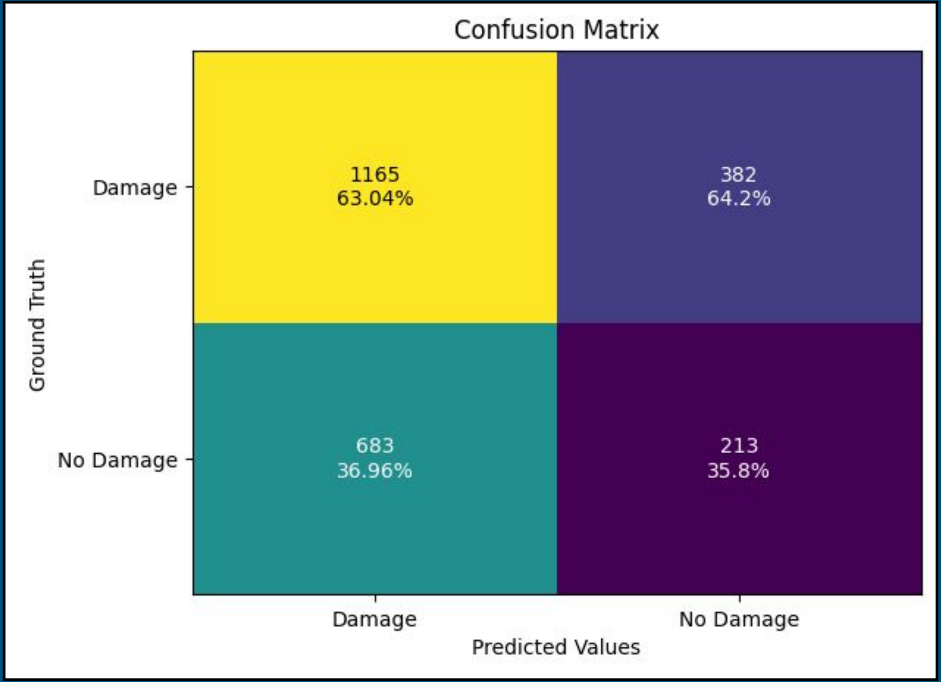
- Lower accuracy but much better guessing pattern
- We found Canny detection more promising than Sobel
- Other filters may be very useful to experiment with in future work



Siamese Network - Results and Takeaways

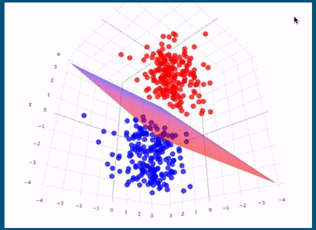
- Binary Classification
  - No-Damage vs Damage
- Complex Model
  - Tuning and adjusting was very difficult and time consuming

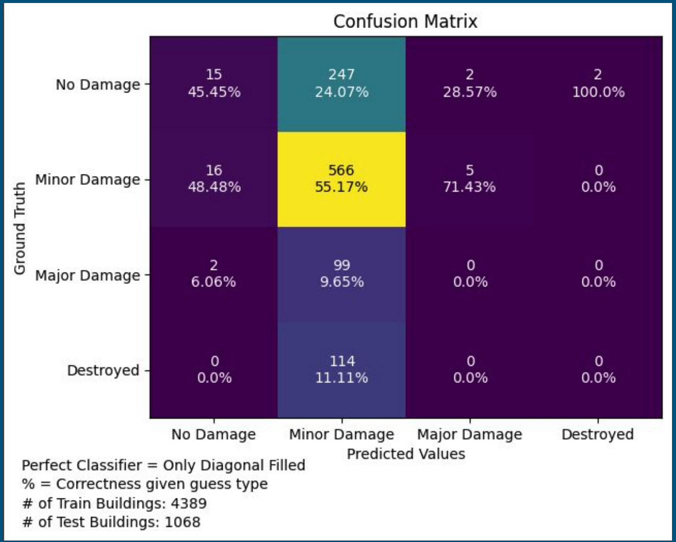




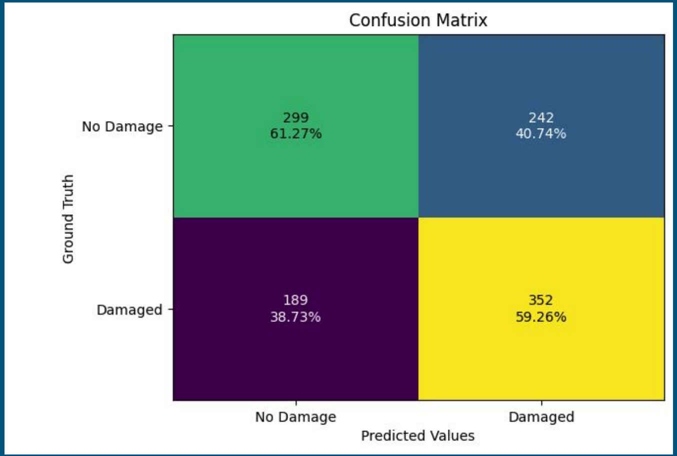
SVM - Results and Takeaways

- PCA
- RBF vs Polynomial Kernels
- Different types of training + testing
    - Baseline
    - Equal Class Split
    - Binary Classification
    - Train on all hurricanes/fires/earthquakes
- Average F1 score of 61%





Mainly guessing the majority class: 54.40%



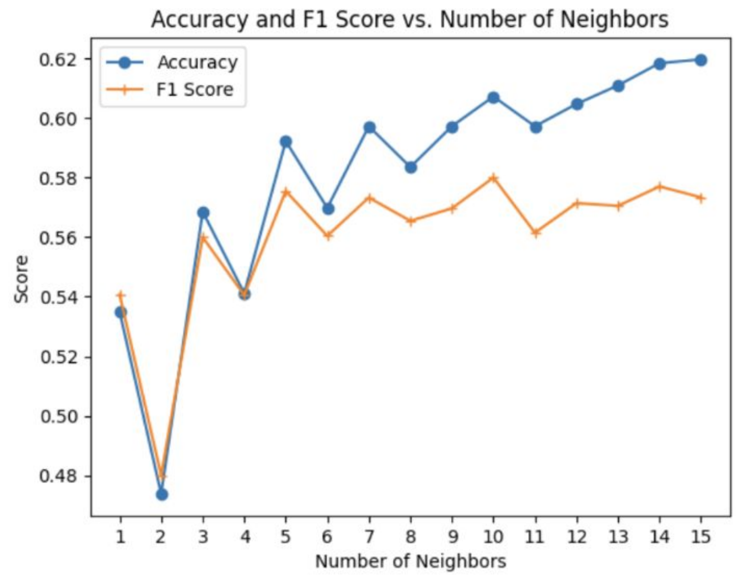
Trained + tested on all hurricanes: 60.17%

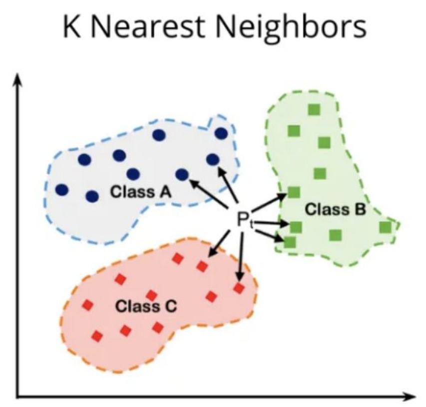
KNN - Results and Takeaways

- Equal Distribution by Damage Label
- Accuracy increases as # neighbors does
- Our F1 score approaches IBM maximum F1 on xView2 dataset

Metric	Score
Localization F_1	0.81
Damage Classification F_1	0.66
Total F_1	0.71

Source: (Alstad, 2020)





(Hurricane Matthew Disaster)

Realistic Constraints

Public Health:
- Disaster Recovery Organizations
- First Responders
- Post-disaster health

Environmental:
- Disaster Types
- Varying Damage
- Location

Global:
- Unequal location distribution
- Developed vs. developing countries

Fairness:
- Proportional Damage Variety
- Infrastructure differences

Economic:
- Disaster preparedness
- Recovery capability
- Damage is relative term by location

Images Sourced from Google Images

Conclusions

- Comparative Analysis of Classification and Traditional Classifiers
    - Accuracy, F1 scores, and Confusion Matrices
- Final Design Choice: KNN!
- Equal Building Distribution was beneficial
- Lessons Learned:
    - Organization
    - Communication
    - Preparation
    - Flexibility
- Further Work

Final Demo

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Thanks

Any Questions?