Utilizing Spatial Data and AI to Help Protect Coastal Communities from Tropical Cyclones

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BACKGROUND

Tropical cyclones are among the most catastrophic natural disasters in the United States. In 2017, Hurricane Maria devastated Puerto Rico, inflicting over $90 billion in damages. Motivated by our direct involvement in disaster relief efforts in Puerto Rico, we sought to contribute to region-specific disaster response strategies. To this end, we developed a building damage detection algorithm using data from San Juan, Puerto Rico, which accurately reflects the region's unique architectural characteristics and damage patterns.

Our model builds upon ESRI's existing machine learning framework, "Building Footprint Extraction, USA," which we enhanced and fine-tuned using high-resolution satellite imagery specific to Puerto Rico. The result was a detection model that significantly improved accuracy compared to the original, unmodified version, with our classification model also demonstrating solid performance.

By making our models publicly available, we aim to provide valuable tools for both first responders and researchers, enabling more effective disaster relief efforts and advancing the understanding of cyclone impacts in the region.

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METHODOLOGY

We approached the problem in two steps: Given a satellite image, we identified buildings in the region of interest (ROI) first, then classified the buildings into damaged and undamaged.

Building Footprint Detection:

We built our model based on an existing building footprint extraction model published by ESRI. To adapt the model to capture the architectural characteristics of Puerto Rico, we incorporated images from Maxar's Open Data Program. This provided our model with satellite images of San Juan before and after Hurricane Maria in 2017, as well as the building footprint shape file.

Initially, we attempted to extract the pixels enclosed by the footprint polygons provided to us and use them as new training data to generate our own model (Method 1 in Figure 1 on the right). However, these building footprints didn't match well with the satellite image, preventing the model from successfully capturing building features. We then downloaded and ran the "Building Footprint Extraction, USA" pre-trained ESRI model (Method 2). Performance was improved, but we decided to fine-tune this model by manually digitizing a large set of building footprints. After supplementing the pre-trained model with about 1800 manually-digitized features and re-training it, we obtained significantly better detection results (Method 3). Figure 1 shows the full progression of our model.

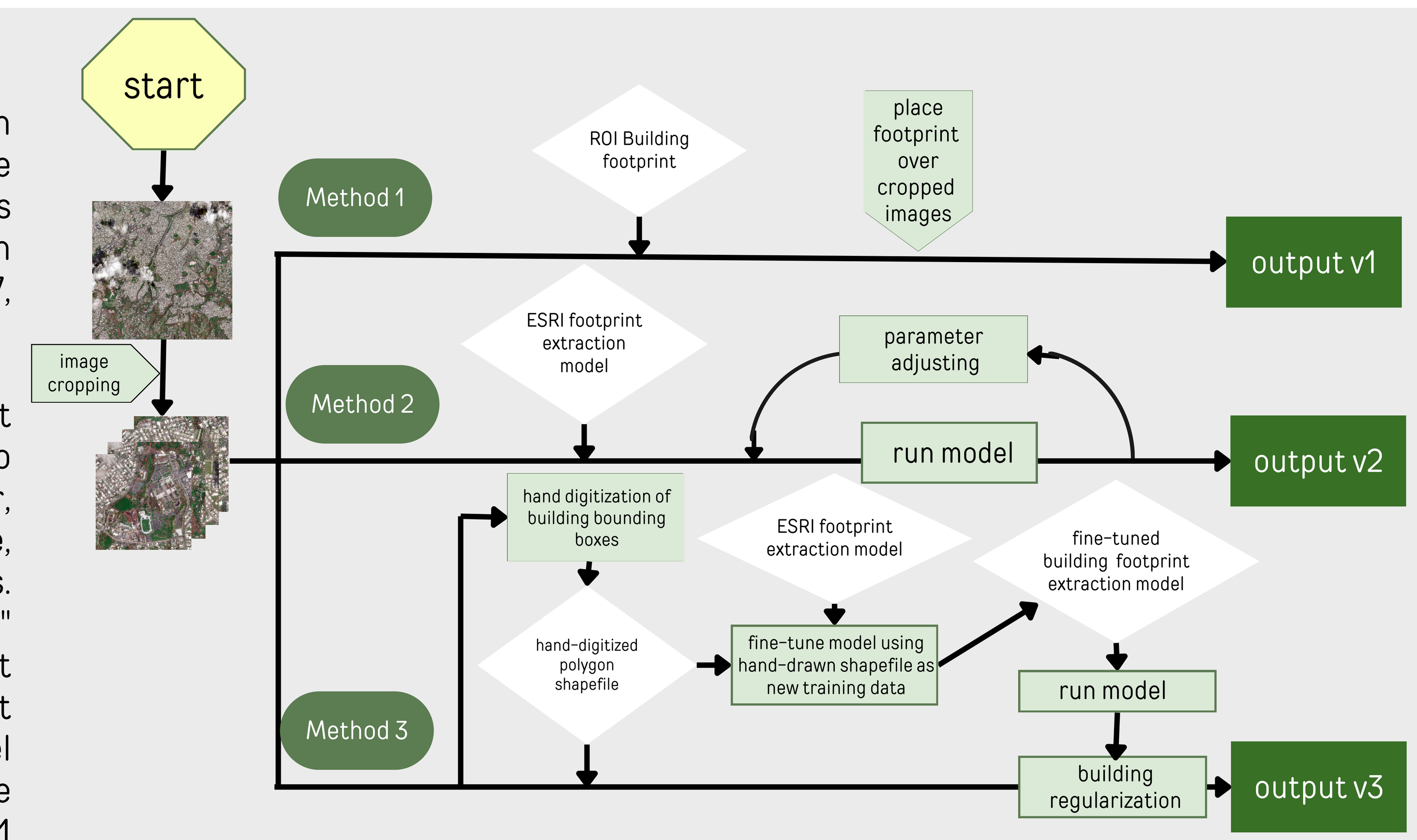

Figure 1. Workflow of developing building footprint detection model using Arc GIS Pro.

Building Damage Classification:

After acquiring an accurate building detection model to extract features, we proceeded to develop a damage classification model. The first step of the process was to generate training data by labeling the building footprints detected by our first model . We labeled 2300+ footprint polygons into "damaged" or "undamaged", and trained our classification model in ArcGIS Pro, using 1800+ footprints. The machine learning architecture we used was **ResNet-34**. After fine-tuning the hyperparameters of the classification model, we tested its performance.

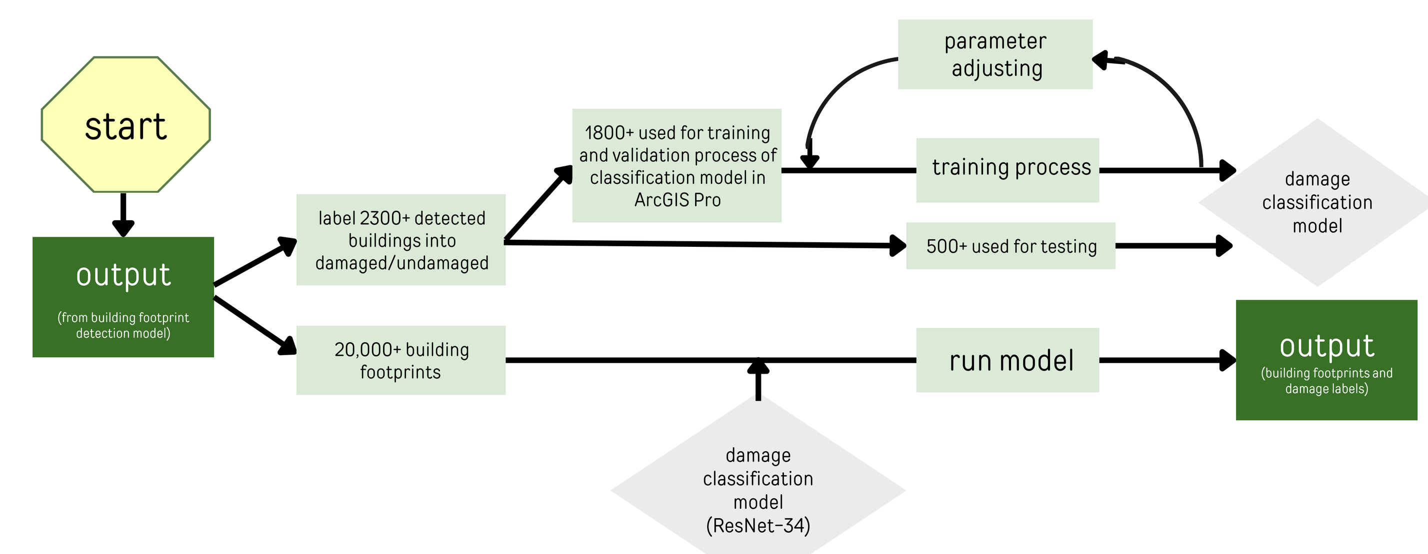

Figure 2. Workflow of developing damage classification model using ESRI Arc GIS Pro.

Figure 3. Visual demonstration of the progress of building footprint detection model over a selected ROI.

The images from left to right are respectively results of:
1: "Building Footprint Extraction - USA" published by ESRI, ran with default parameters.
2: "Building Footprint Extraction - USA" published by ESRI, ran with fine-tuned parameters.
3: Our fine-tuned building footprint detection model and optimized parameters.
4: The previous result after applying building regularization (rectangularize) in ArcGIS Pro.

RESULTS

Building Footprint Detection Model:

During the training process, we implemented an early-stopping strategy to stop the model training once its performance ceased to improve. The training concluded after 19 epochs, achieving an average precision of 0.535. This approach effectively minimized the risk of overfitting while ensuring optimal model performance.

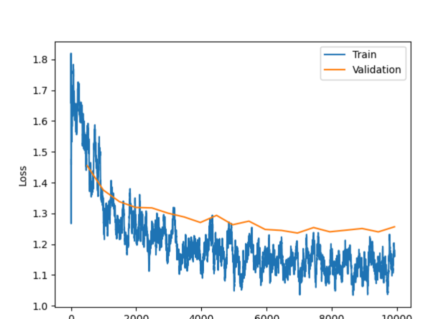

Figure 4. (left) Graph of training and validation loss of our building detection model.

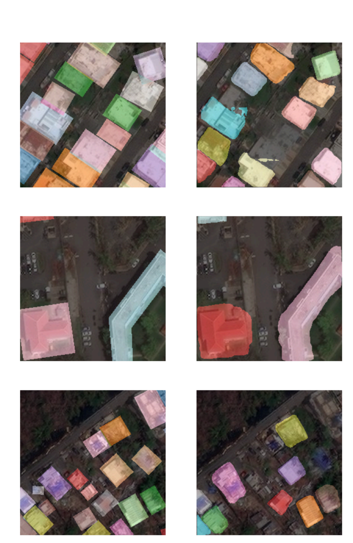

Figure 5. Comparisons between ground truth building footprints (left) and predicted building footprints (right).

Damage Classification Model:

The model achieved an overall accuracy of 79% in classifying damaged and undamaged buildings, with a precision of 34%, a recall of 71%, and an F1-Score of 46% for the damaged class.

Accuracy measures the model's overall correctness, while precision indicates the percentage of predicted damaged buildings that were correctly identified as damaged. Recall reflects the percentage of actual damaged buildings that the model correctly classified. The F1-Score, as the harmonic mean of precision and recall, provides a balanced measure of the model's effectiveness in detecting damaged buildings.

		Predicted	
		undamaged	damaged
Actual	undamaged	369	94
	damaged	20	48

	Precision	Recall
undamaged	0.95	0.80
damaged	0.34	0.71

Figure 6. Confusion matrix (at the top) and classification report (at the bottom) for the damage detection model.

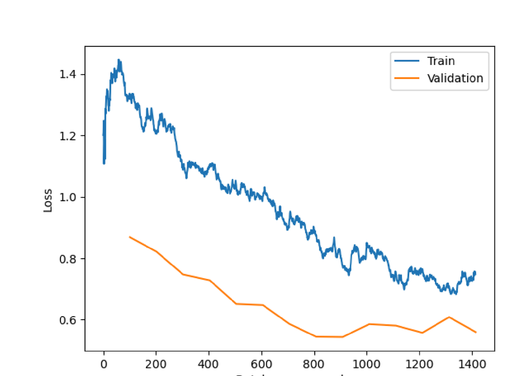

Figure 7. Graph of training and validation loss of our building detection model.

Figure 8. Example of the result of our building damage classification model. Green indicates undamaged, and red indicates damaged.

DISCUSSION

- The performance of our building detection model is significantly affected by the quality of the data. It is hard to extract features from buildings that are under the shade or covered by the clouds. In the future, it's worth looking into ways that can improve the quality of spatial data.

Figure 9. Picture of the high-resolution satellite data of San Juan used in this research. Image has visible clouds and shadows.

- There are several reasons why our classification model's performance may be affected:
  - Unbalanced training data with 1/8 in the set labeled as damaged and 7/8 as undamaged buildings
  - Poor spatial data quality: shadows, clouds, etc.
  - The variability in our manual labeling can also affect our model's precision, as the model may be learning from labels that are not perfectly consistent
- Though our model is tailored to Puerto Rico's architecture, the real value of our research is in developing a method for creating region-specific models. We believe models customized to local architectural styles will outperform generic ones, offering better adaptability across different regions and evolving designs.
- A big hurdle is being able to identify which buildings are damaged versus which are undamaged when annotating the features. For anyone who wishes to develop on our research, it is paramount that they have some on the ground truth data in order to make sure their model is learning correctly.
- If given both pre-storm and post-storm images, another way to increase accuracy is to build a model that can detect the changes of building conditions before and after the natural disaster.

CONCLUSION

- We optimized two models: one that detected buildings and one that classified them based on damages.
- The two-step model is preferable due to the ability to fine tune each model to its specific task, compared to a model that attempts to do both.
- Additional work is necessary to improve the quality of imagery for building detection and the quality of training data for damage classification.
- Due to time constrains, we were unable to formulate a new model; however, we acquired valuable knowledge by applying existing models in various contexts. This approach yielded significant insights, enhancing our understanding of potential future directions for research.

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