Automated mapping of hurricane roof damage using deep learning and drone imagery: An end-to-end Esri ArcGIS Pro workflow

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Motivation

Roof damage from major storms needs to be quickly identified and repaired to allow residents to continue living in their homes. Traditional, ground-based inspections of roof damage are time-consuming, but have recently been expedited via manual interpretation of remote sensing imagery. To further quicken the process, artificial intelligence (i.e., deep learning) can be applied (Fig. 1). **The objectives of this research are to train and evaluate a deep learning model that performs automated detection and delineation of two classes of post-storm roof damage: roof decking and roof holes.**

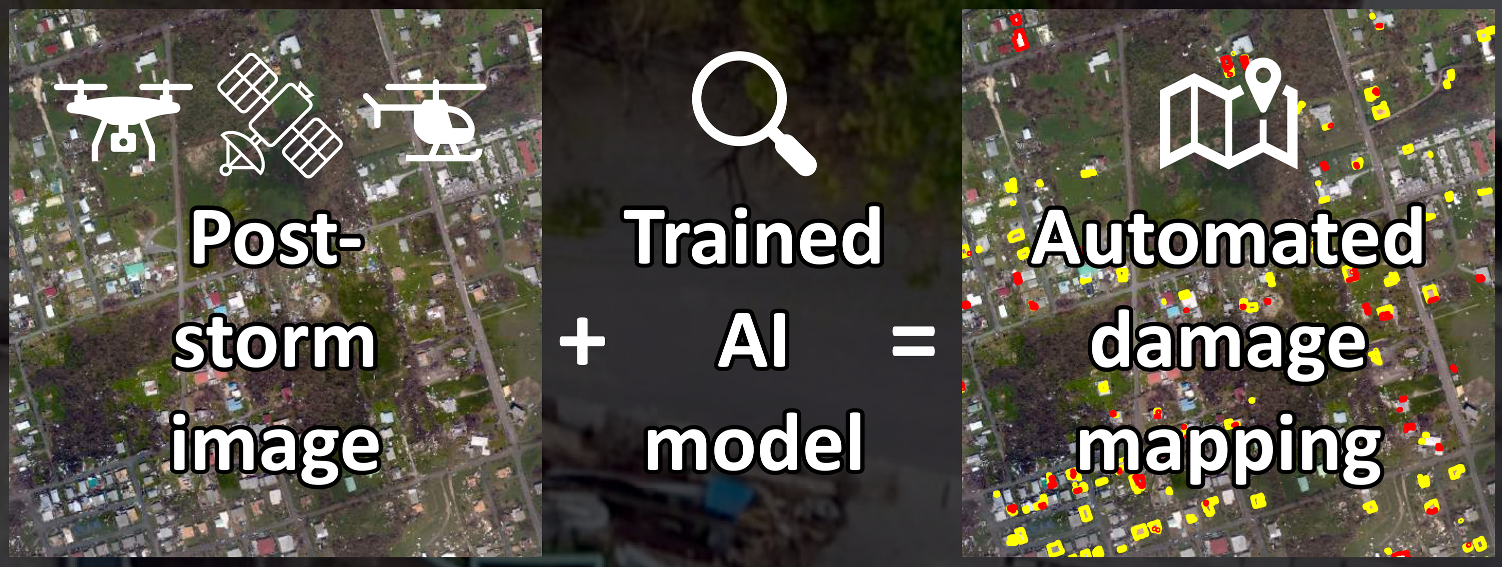

Figure 1. Remote sensing imagery of storm-affected areas can be combined with a trained artificial intelligence (AI) model to automatically map roof damage. Image: NGS (2022)

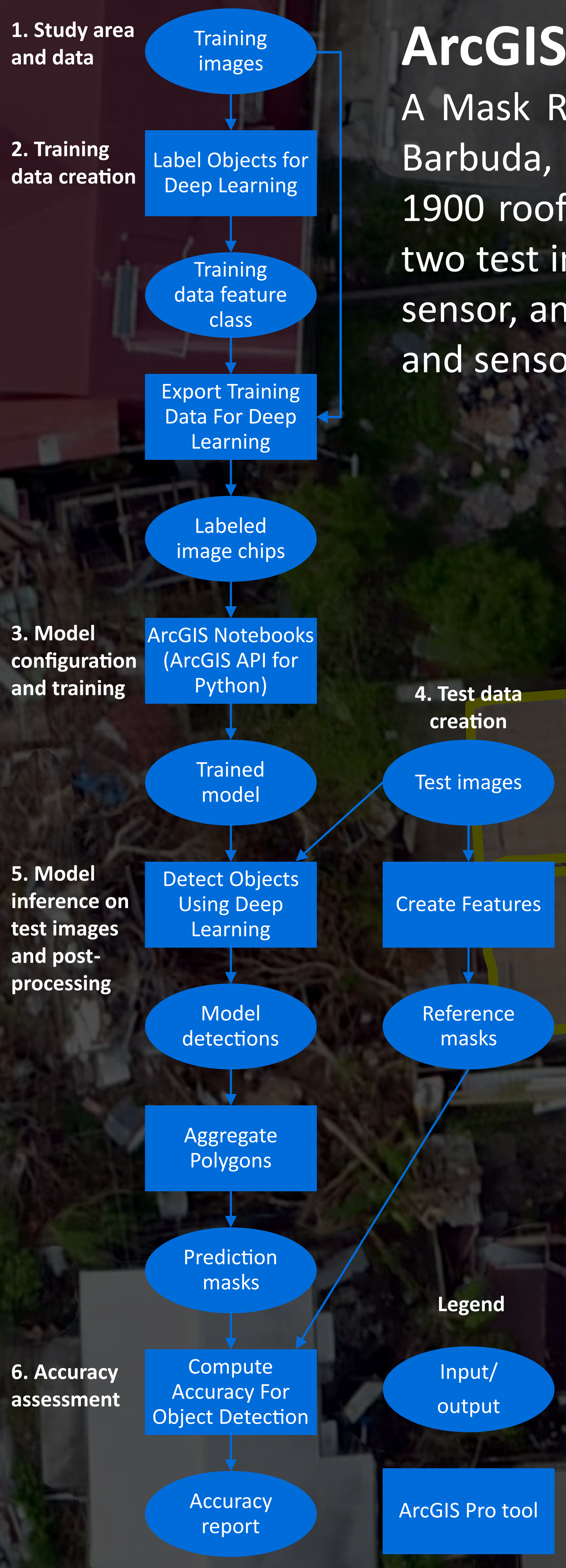

Figure 2. Workflow showing inputs/outputs (ovals) and ArcGIS Pro tools (rectangles).

ArcGIS Pro workflow

A Mask R-CNN model was trained (Fig. 2) using drone orthomosaics captured in Sint Maarten, Antigua and Barbuda, and Dominica following Hurricanes Irma and Maria in 2017. Training data were created by digitizing 1900 roof decking objects and 1300 roof hole objects (Fig. 3). The trained model was evaluated (Fig. 2) using two test images: one captured within the general training area in Sint Maarten by the same drone platform and sensor, and another captured outside the training area in the United States Virgin Islands with a crewed aircraft and sensor that were not used during training.

Figure 3. Examples of training samples delineating roof decking (yellow polygons) and roof holes (red polygons). Image: GlobalMedic (2022)

Preliminary results

- F1-score (overall accuracy): 75% in both test areas (Table 1)
- Higher F1-scores: roof holes
- Higher precision (prediction correctness): Sint Maarten
- Higher recall (prediction completeness): US Virgin Islands
- Figure below shows examples of false positives and negatives

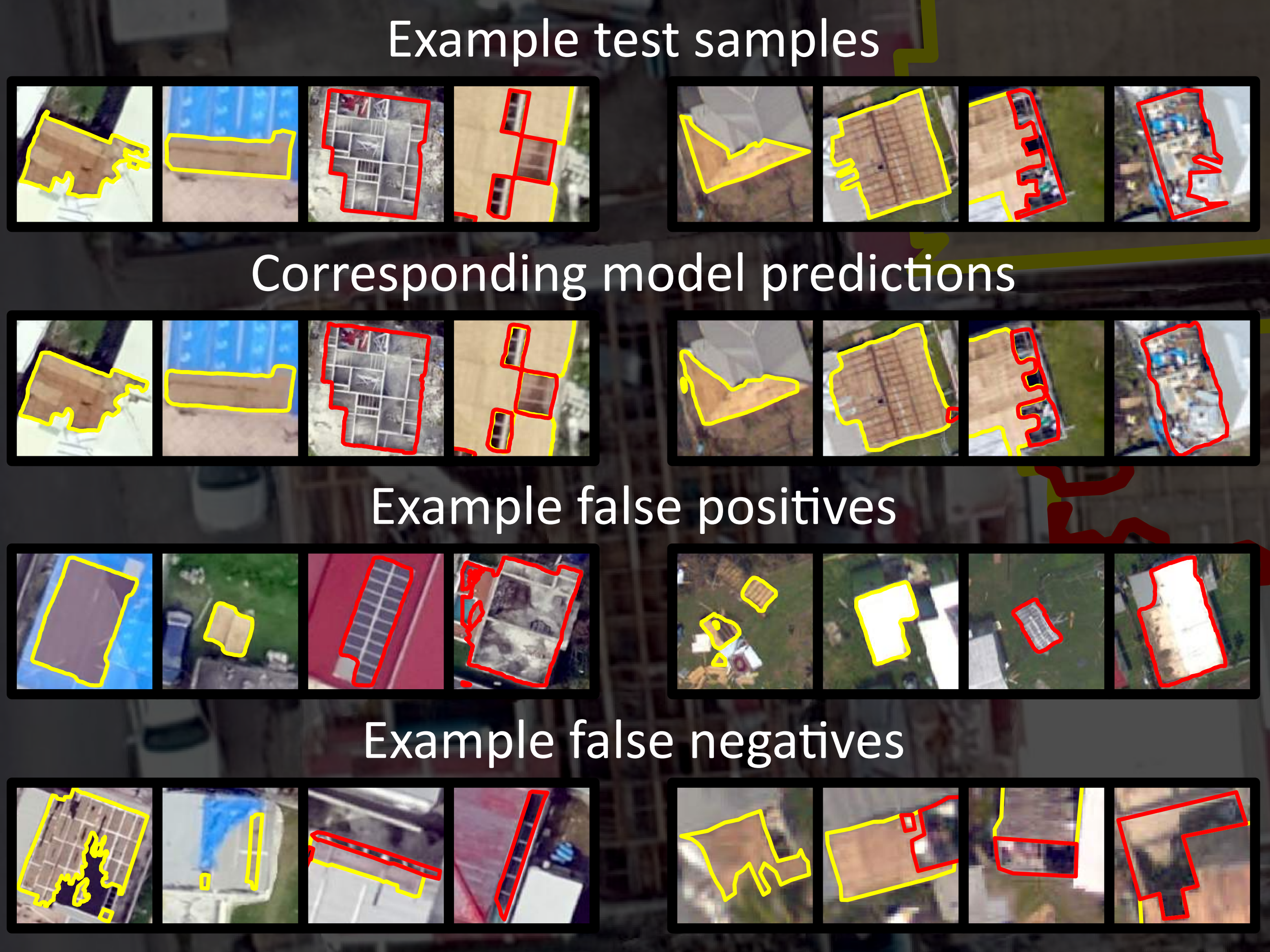

Table 1. Accuracy assessment results for the Sint Maarten (SM) and US Virgin Islands (USVI) test images.

Parameter	SM	USVI	SM	USVI	SM	USVI
	Decking		Hole		Both classes	
True positives	34	74	23	51	57	125
False positives	10	48	3	16	13	64
False negatives	17	8	8	11	25	19
Precision	0.77	0.61	0.89	0.76	0.81	0.66
Recall	0.67	0.90	0.74	0.82	0.70	0.87
F1-score	0.72	0.73	0.81	0.79	0.75	0.75

Future work

- Expand the training dataset to increase representation of undetected objects and to reach class balance
- Expand testing to larger areas, geographies outside the Caribbean, and various spatial resolutions of imagery to assess the transferability of the model

For more information, visit the story map:

Acknowledgements

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References

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- NGS. (2022). 2017 NOAA NGS Emergency Response Imagery: Hurricane Maria. https://www.fisheries.noaa.gov/inport/item/52283