

# Remote Assessment of Parking Areas for PV Canopies with Deep Image Segmentation and Minimum Bounding Rectangle Polygonization

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## Introduction

There are large areas of uncovered parking lots throughout urban centers. These present an opportunity to use solar photovoltaics (PV) to shade the parking spaces in these lots while at the same time providing distributed power generation. This poster describes a method for quantifying the technical potential of PV canopies over uncovered parking lots using remote imagery. We created a deep image segmentation model, polygonised the model outputs, and assessed the accuracy of the final system output.

An “image segmentation” machine learning (ML) model accepts an image as an input, then assigns each pixel of the image to a set of two or more classes by assigning a probability to each possible class. Image segmentation has been applied to parking areas in [1] and [2] to infer the number of available parking spaces. Dowling explored PV technical potential using GIS analysis alone [3].

## Methods

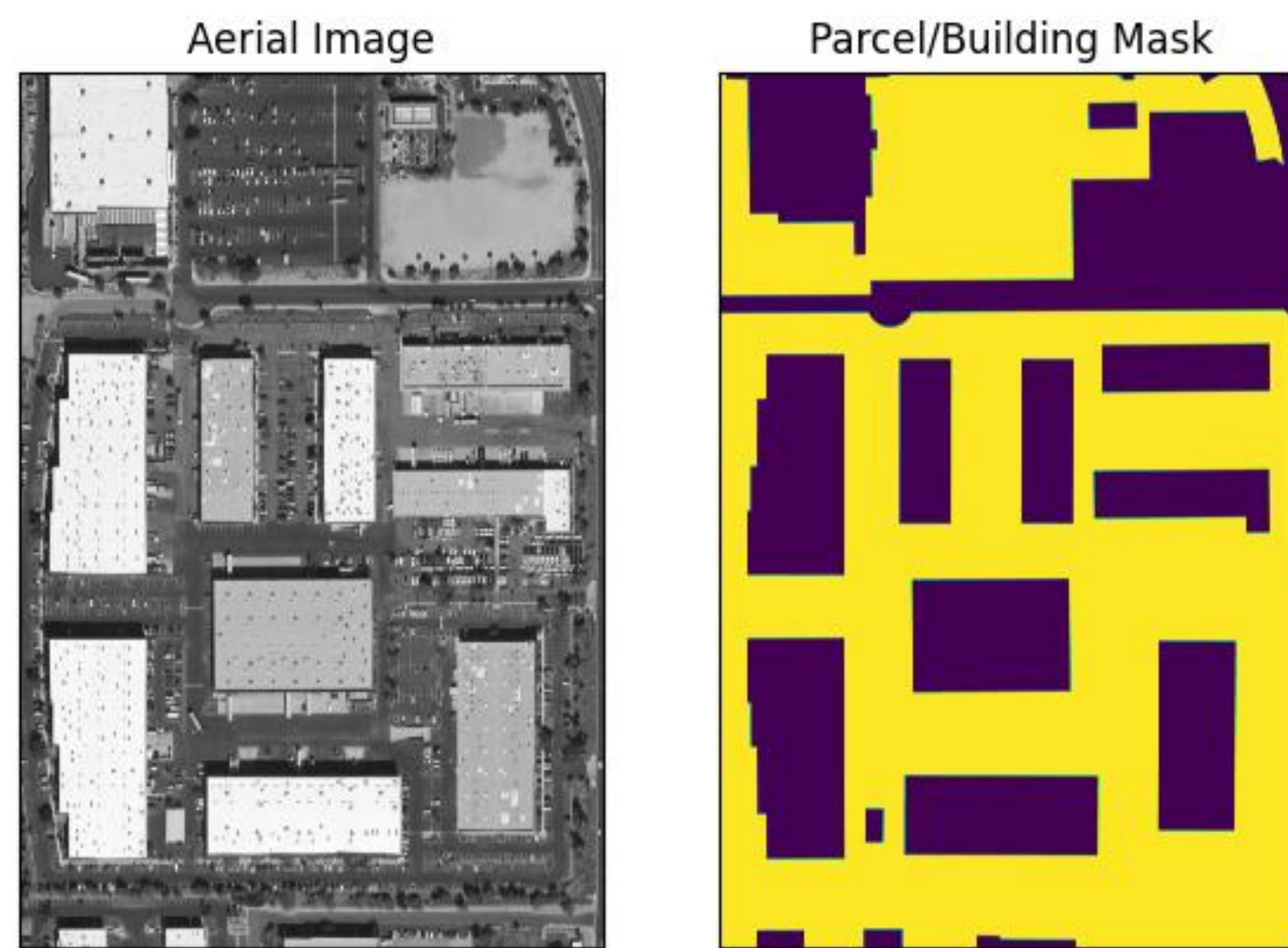


Fig. 1. Left: High-resolution aerial image converted to grayscale. Right: Image mask identifying image regions potentially suitable for parking area PV classification. (yellow: suitable, purple: not suitable).

From a set of 1,144 20k-by-20k pixel (5,000 ft. x 5,000 ft.) high-definition aerial images covering an urban area, six were selected and manually labeled. This created a “ground truth” set of images with known parking area polygons. The RGB aerial images were converted to grayscale. A parcel type (e.g., “residential”, “commercial”, “park”) layer and building footprint layer were combined to create a mask identifying areas not considered viable for parking area PV (Fig. 1).

Each of the combined image and mask arrays were subdivided into 1,521 512 x 512 tiles for training of the deep segmentation machine learning model. A Scharr edge filter [4] was applied to the grayscale layer and masked with the parcel/building layer (Fig. 2).

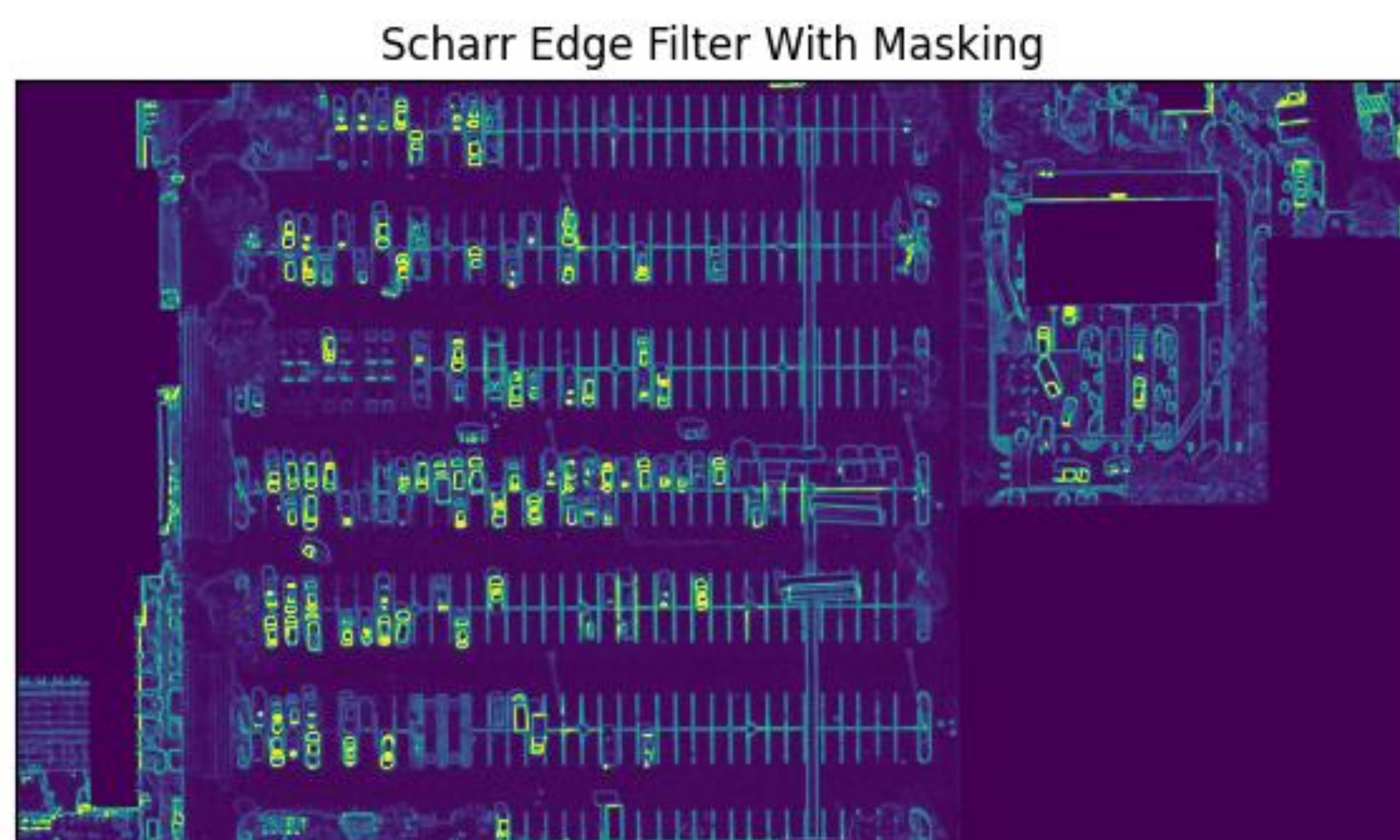


Fig. 2. Scharr edge filter applied to high-resolution grayscale image.

## Creating the Deep Image Segmentation Machine Learning Model

We created a U-Net [5] model with 2 million trainable parameters with TensorFlow. The model was trained with the 512 x 512 Scharr filtered [5] arrays as features and 512 x 512 arrays classifying each pixel as either valid for parking area PV, or not valid, as targets. The output of the trained model was a 512 x 512 array predicting the probability that each input pixel is within a parking area. Fig. 3 shows the output of segmentation model for a section of the validation set and the corresponding “ground truth” of the same area. To recreate a 20k-by-20k output from multiple 512 x 512 output tiles, tiles were mosaiced with overlapping edges to minimize boundary effects. We created segmentation model outputs for all six images using leave-one-out cross-validation, leaving out one of the images from the training set for each fold.

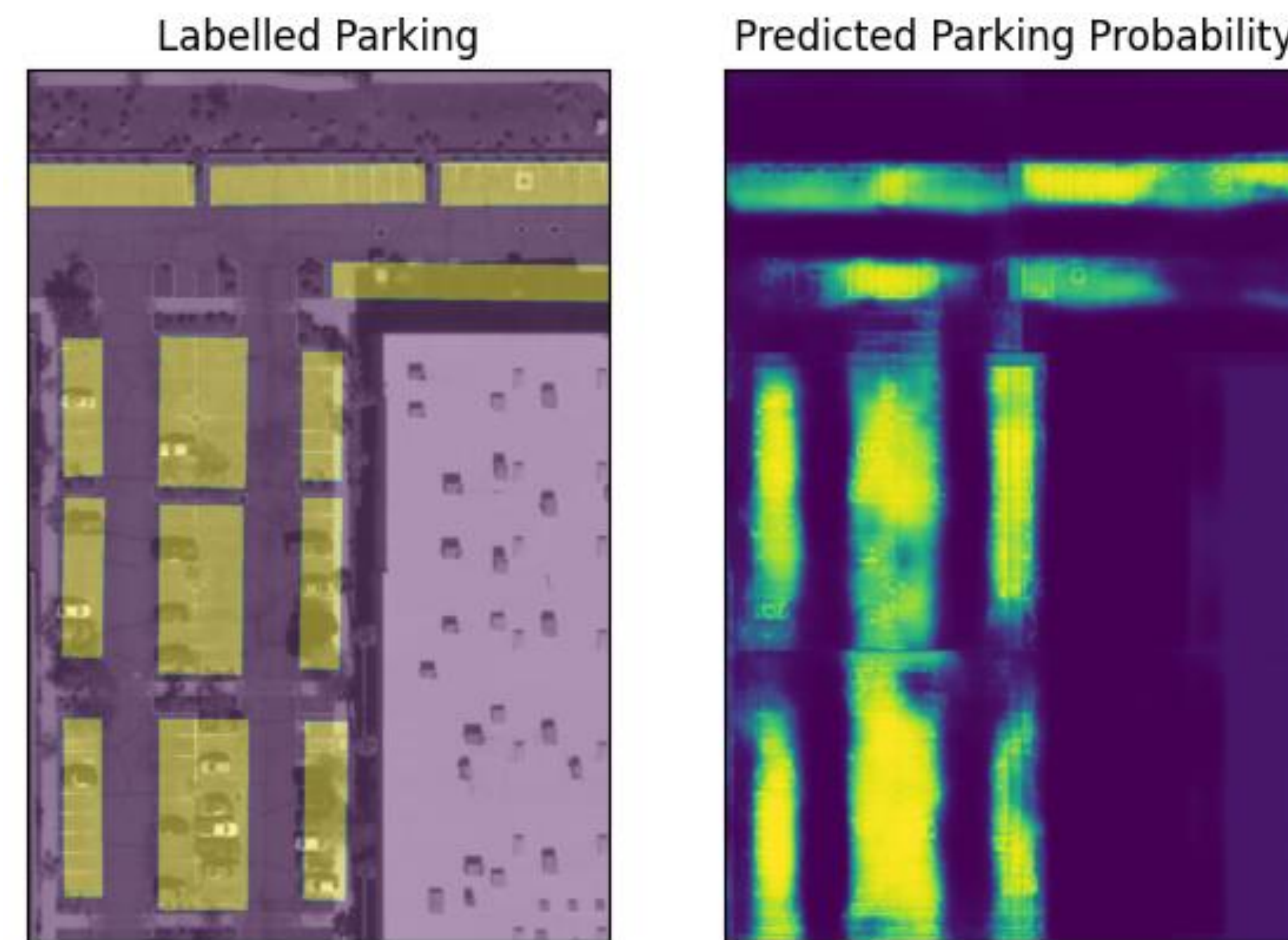


Fig. 3. Left: “Ground Truth” manually created parking area polygons. Right: Segmentation model output from cross-validation validation set outputs. The brighter areas indicate a higher estimated probability that the pixel is within a parking area.

## Polygonization of Segmentation Model Outputs

The image segmentation output (a per-pixel probability of the presence of a parking area) was converted to a binary classification at multiple threshold probabilities. The binary pixel classifications were then converted to polygons by identifying minimum bounding rectangles for continuous clusters of parking area pixels. These bounding polygons were filtered by size, keeping only polygons above a cutoff size.

## Results

The segmentation-derived polygons were evaluated against the “ground truth” polygons using the Intersection over Union metric (IoU). IoU is a measure of accuracy used to assess skill in object detection. The IoU between the estimated parking regions  $R_{est}$  and the actual regions  $R_{act}$  is shown in (1).

$$IoU = \frac{R_{est} \cap R_{act}}{R_{est} \cup R_{act}} \quad (1)$$

Parking area classification IoU was evaluated for classification threshold probabilities from 0.3 to 0.95, and minimum polygon areas of 0, 200 and 500 sq. ft. (Fig. 4). A classification threshold at 0.698 and a minimum bounding rectangle size of 200 sq maximized IoU. The spatial true positive rate (2) was 74.8%. The false positive rate (3) was 2.9%. The false negative rate (4) was 25.1%. The true negative rate (5) was 97.1%.

$$true\ positive\ rate\ (TPR) = \frac{R_{est} \cap R_{act}}{R_{act}} \quad (2)$$

$$false\ positive\ rate\ (FPR) = \frac{R_{est} - R_{act}}{R_{total} - R_{act}} \quad (3)$$

$$false\ negative\ rate\ (FNR) = \frac{R_{act} - R_{est}}{R_{act}} \quad (4)$$

$$true\ negative\ rate\ (TNR) = \frac{R_{act} \cap R_{est}}{R_{act}} \quad (5)$$

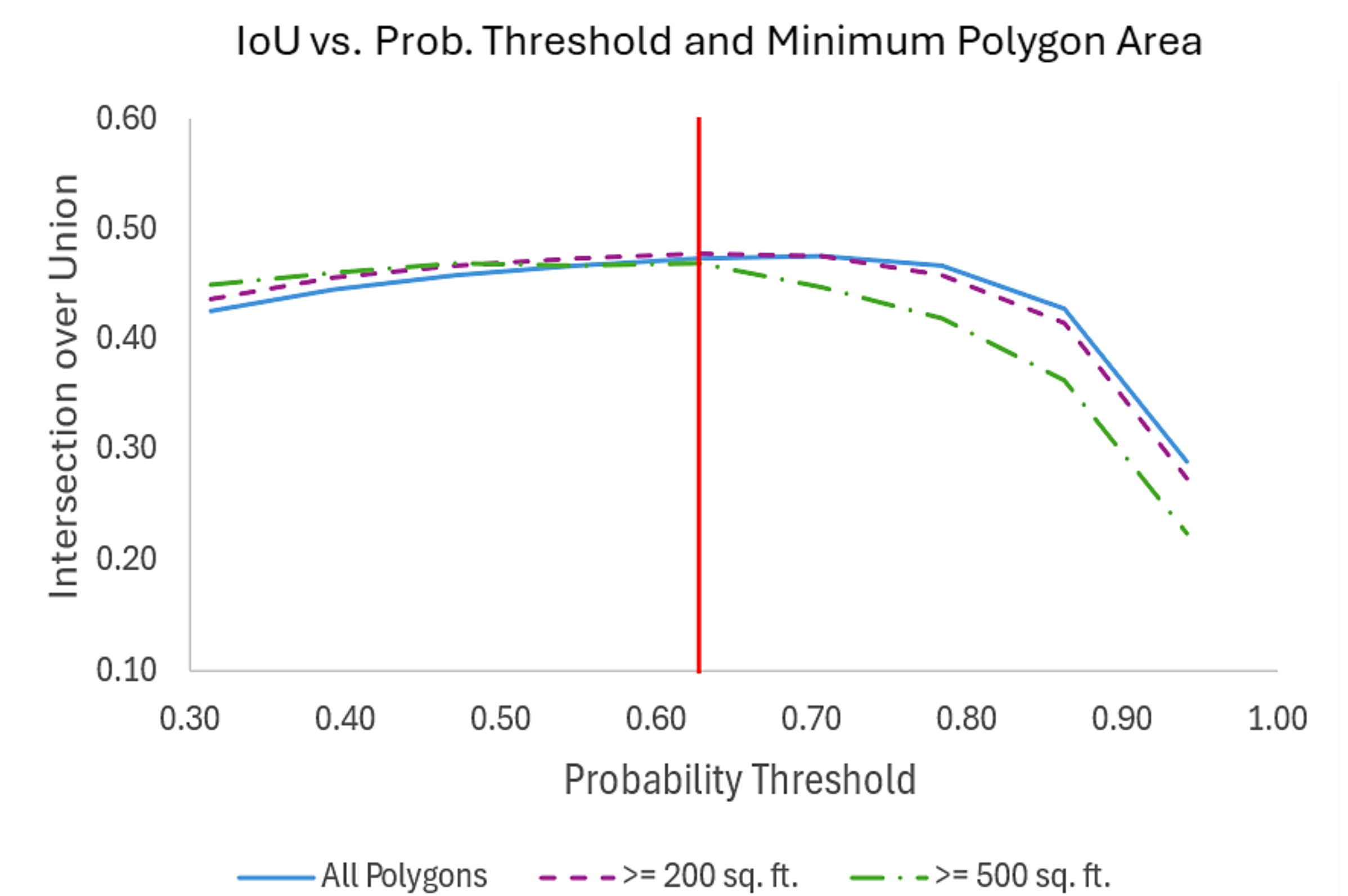


Fig. 4. Intersection over Union at multiple classification thresholds and minimum parking area polygon sizes. The probability threshold at 0.698 with a minimum rectangle area of 200 sq. ft. maximized IoU.

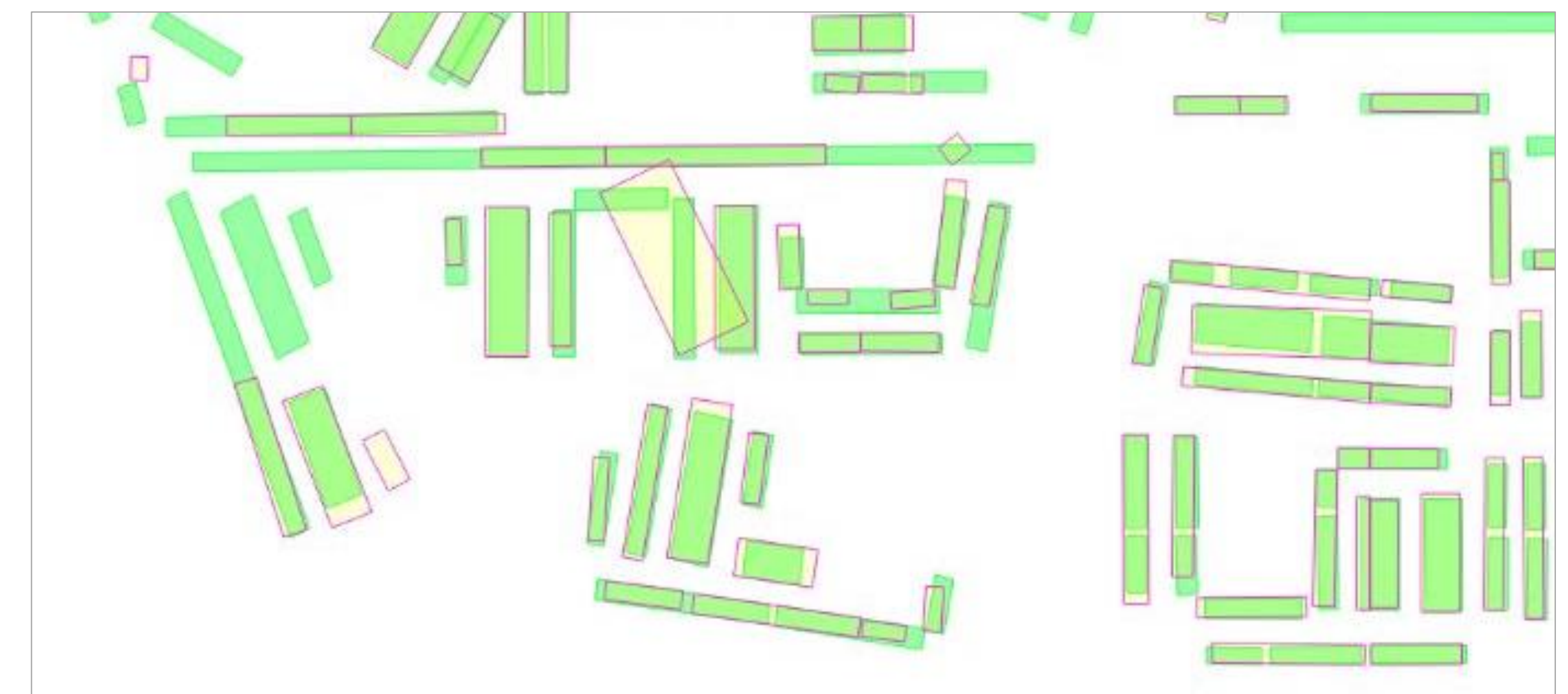


Fig. 5. Ground truth parking areas (green) shown with estimated parking areas (yellow, red outline) for the optimal polygonization criteria.

Fig. 5 shows the estimated parking area polygons and the ground truth parking areas. False positive areas were largely caused by convergence of adjacent parking areas during the pixel classification stage causing faulty polygon boundaries during polygonization. Some ground truth parking areas are missed due to tree shading of parking space lines confusing the segmentation model.

## Conclusion

Combining deep image segmentation with minimum bounding rectangle polygonization effectively characterized parking areas suitable for PV canopies. Using a U-Net deep image segmentation architecture with an output classification threshold of 0.698 and a minimum parking area size of 200 sq. ft., we achieved an IoU of 0.643 and a false positive rate of 2.9%. We believe these error rates can be reduced with more varied training data (e.g. more training examples of parking obscured by trees). This methodology allows utilities and policy makers to quantify the potential for PV power at a large geographical scale from aerial image surveys.

## References

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