Deep Learning-Based Honeybee Hive Classification

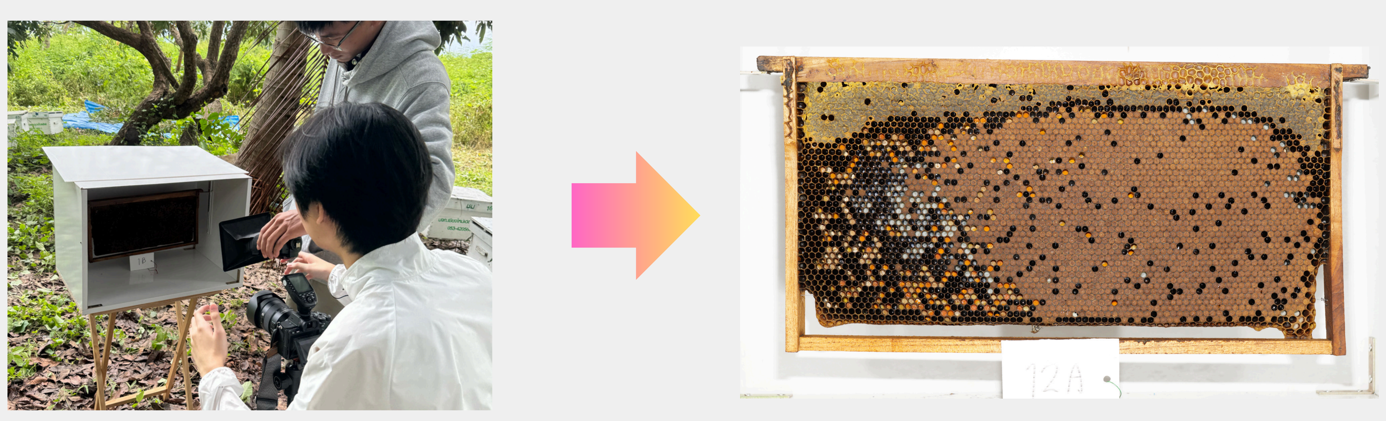
Panpakorn Kritangkoon[1]
Advisor: Asst.Prof.Dr. Watit Khokthong, and Assoc.Prof.Dr. Terd Disayathanoowat[2]
[1]*Environmental Science Program, Faculty of Science, Chiang Mai University, Chiang Mai, 50200, Thailand*
[2]*Department of Biology, Faculty of Science, Chiang Mai University, Chiang Mai, 50200, Thailand*
**Contact: panpakorn_k@cmu.ac.th, Corresponding author: tae.watit@gmail.com*

Abstract

Traditional honey assessment is typically conducted through visual inspection by farmers, which can be inconsistent due to varying levels of experience and different phases of honey production. With the growing demand for honey products, image processing offers an efficient alternative for estimating honey quantity. This study presents a machine learning based method utilizing image processing to quantify honey areas inside the red, green, and blue (RGB) images captured with a consumer-grade camera (Sony, a7R IV, 2019). Monthly image collections were conducted between July 2024 and January 2025. YOLO version 11 was applied to the 464 honeycomb images for enabling automated detection and classification of capped and uncapped honey cells. Moreover, 64.6% of honeycomb images were used to train and validate the model. For masking capped honey cells, the mean average precision (mAP) at an intersection over union at threshold of 0.5 was 80.5%. For masking uncapped honey cells, the mAP50 was 74.3%. Using bounding box detection, the mAP50 score was 80.5% for capped honey cells and achieved the highest performance for uncapped honey cells at 83.4%. This method offers a reliable, scalable solution for real-time honey quantity assessment, significantly enhancing beekeeping efficiency through automated monitoring of honey production.

Method

1. A DIY wooden studio box with a Flash Godox TT685 TTL ensured consistent lighting. A Sony A7R4 captured 60MP images (9504x6336px).



2. 300 images were annotated using X-AnyLabelling and uploaded to Roboflow.

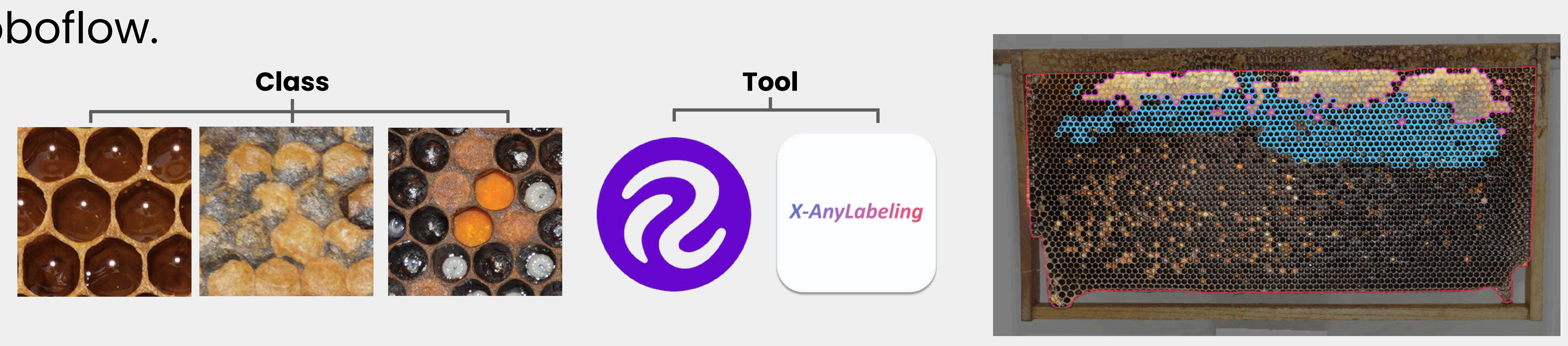
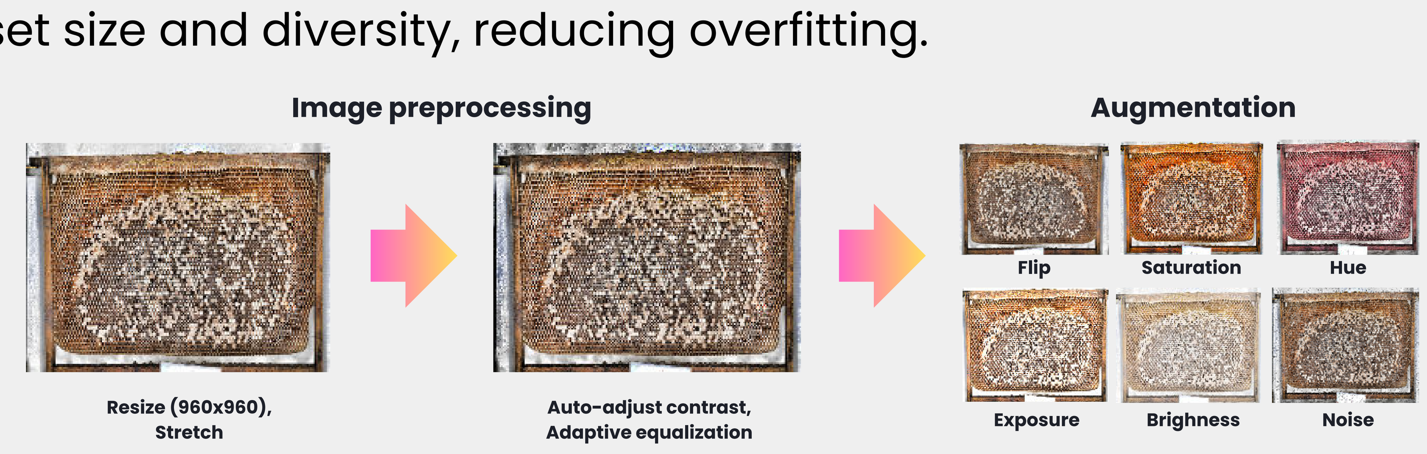


Table 1 lists the annotated classes, with polygons drawn around objects of interest.

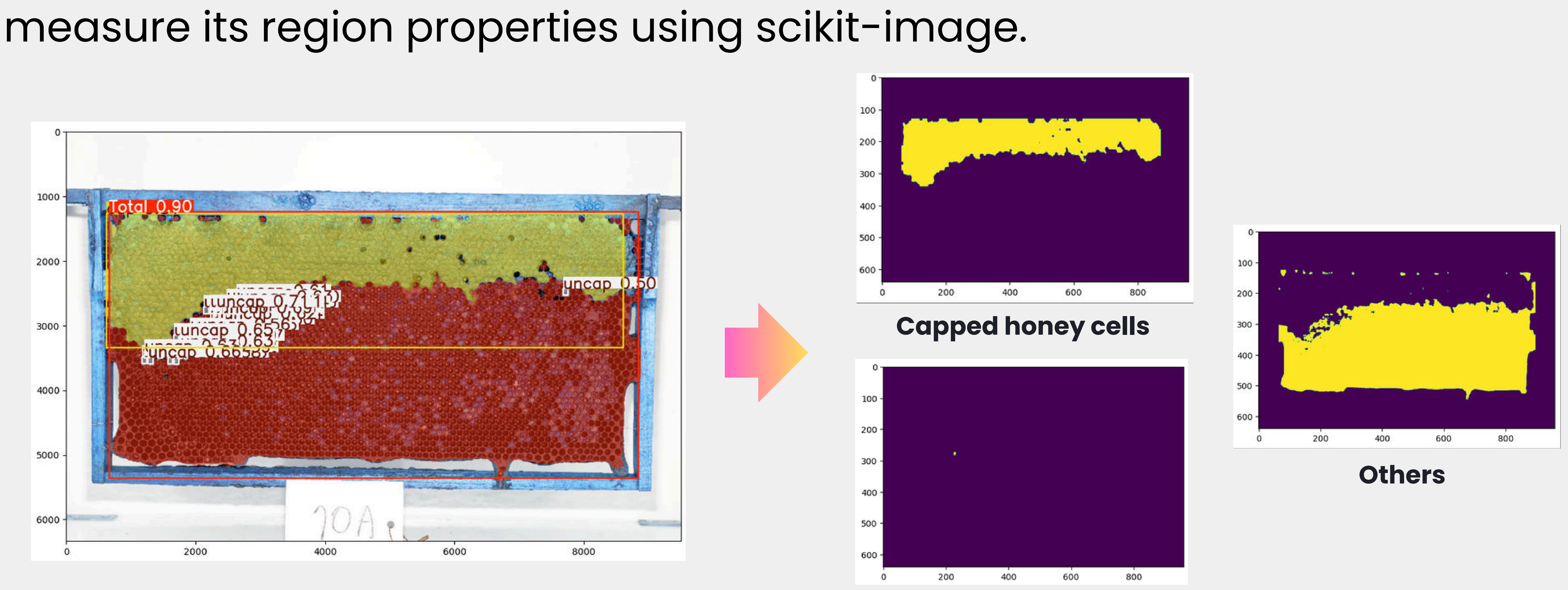
Class	Description	Number of Annotation
uncap	Polygon around the honey-uncapped cell	62520
cap	Polygon around the honey-capped cell	607
other	Polygon around the area of the bee wax	300

3. The annotated dataset was resized for model compatibility. Augmentation techniques like flipping, rotating, and altering image properties increased dataset size and diversity, reducing overfitting.



4. This study used YOLOv11s-seg for object detection, segmentation, and validation. The dataset was split (90% train, 5% validation, 5% test). Training on an NVIDIA 3070 Laptop GPU (8GB). Models were tested with various input sizes (960×960 to 256×256) and batch size 4 over 200 epochs to optimize performance.

5. After predicting the image, we extract each class's segment area and measure its region properties using scikit-image.



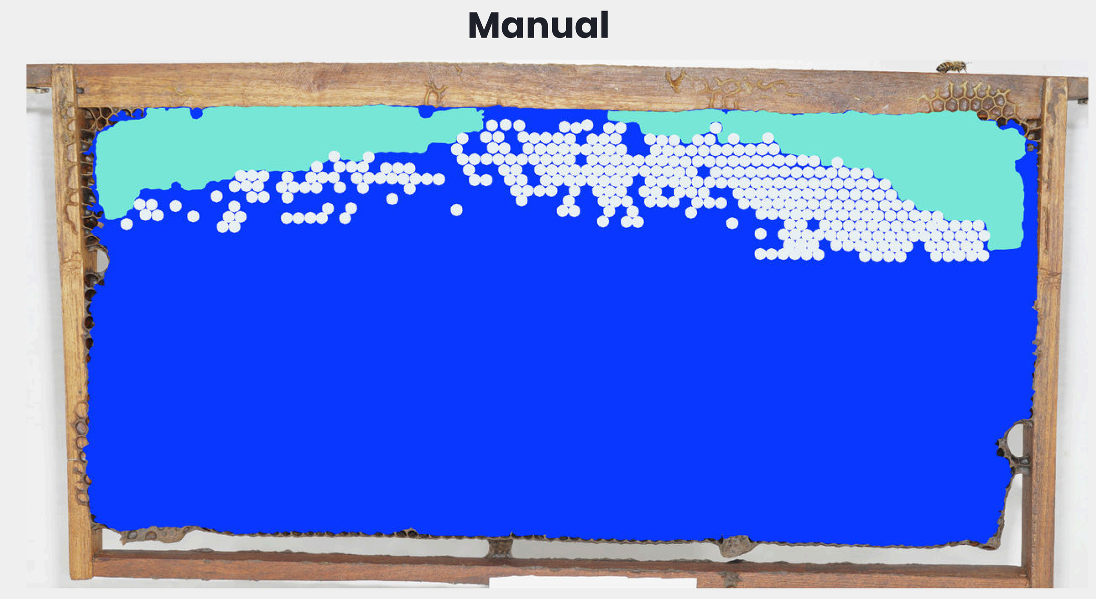
Results & Discussion

1. These table show a clear trade-off between input image size, training time, and detection performance.

Image size	Training Time (hr)	mAP50			
		Uncapped honey cells		Capped honey cells	
		Box	Mask	Box	Mask
960×960	13.39	0.834	0.743	0.805	0.805
800×800	3.13	0.842	0.513	0.775	0.681
640×640	1.76	0.773	0.434	0.790	0.720
512×512	1.76	0.655	0.273	0.685	0.638
256×256	1.39	0.229	0.028	0.505	0.378

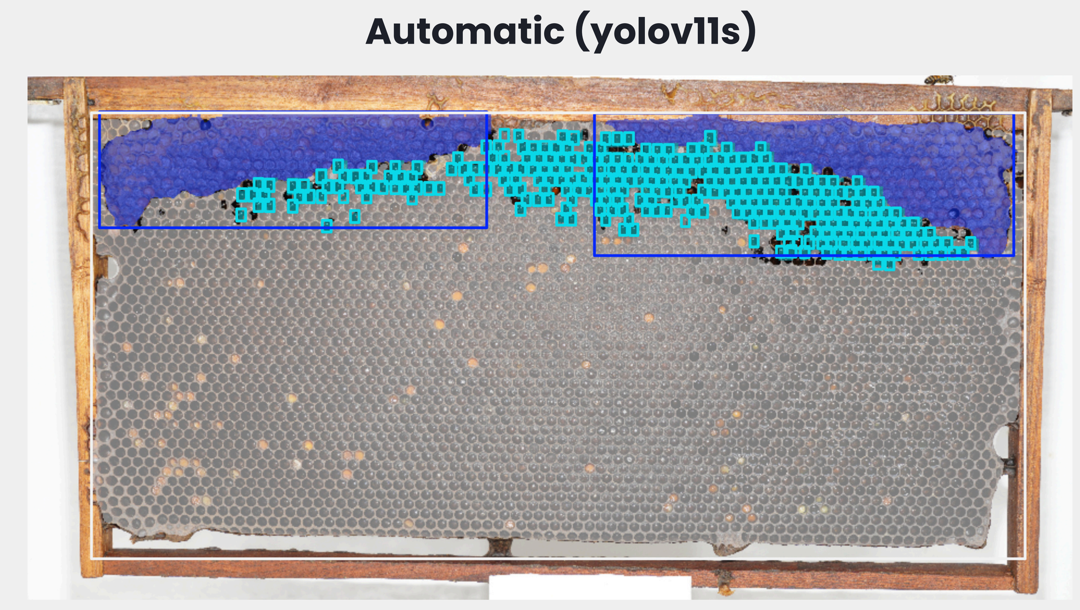
2. This comparison shows that the YOLOv11s-seg model provides similar results to manual labeling, demonstrating its potential for automating honeycomb analysis with minimal error (Image ID = _DSC5334).

Manual



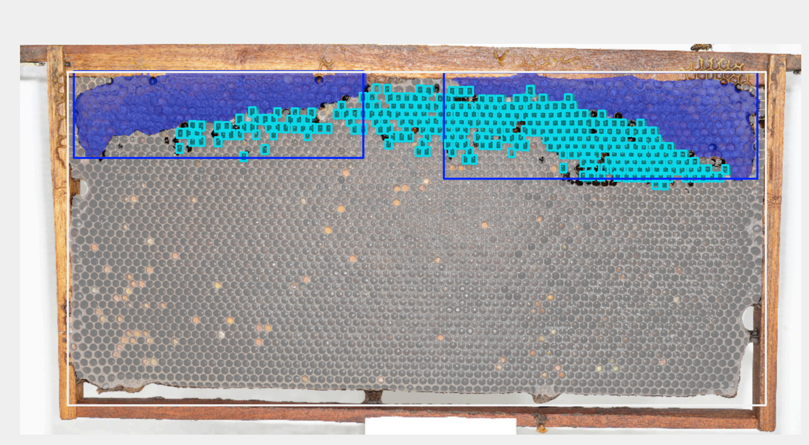
uncapped = 352, capped = 2, others = 1

Automatic (yolov11s)



uncapped = 297, capped = 2, others = 1

3. Example of the percertage of honey areas calculating the mask.



$$\text{Honey area (\%)} = \frac{\text{capped + uncapped}}{\text{(capped + uncapped + others)}} * 100$$

$$\text{Honey area (\%)} = \frac{39423 + 36207}{(39423 + 36207 + 253991)} * 100$$

Honey area (%) = 29.944 %

Conclusion

The study shows that YOLOv11s reliably detects and classifies honeycomb cells, achieving mAP50 scores of 80.5% for capped and 83.4% for uncapped cells—nearly matching manual labeling. Although larger input sizes improve accuracy, they require longer training times. Overall, integrating deep learning with image processing provides an efficient, scalable method for real-time honey assessment, offering a strong alternative to traditional inspections.

Source Reference

- Alves, T. S., Pinto, M. A., Ventura, P., Neves, C. J., Biron, D. G., Júnior, A. C., De Paula Filho, P. L., & Rodrigues, P. J. (2020). Automatic detection and classification of honey bee comb cells using deep learning. Computers and Electronics in Agriculture, 170, 105244. https://doi.org/10.1016/j.compag.2020.105244