American Society of Agricultural and Biological Engineers
2950 Niles Road | St. Joseph MI 49085-9659 | USA
269.429.0300 | fax 269.429.3852 | hq@asabe.org | www.asabe.org

*An ASABE Meeting Presentation*
***DOI: https://doi.org/10.13031/aim.202500146***
***Paper Number: 2500146***

# Application of Deep Learning in Counting and Gender Identification of Parasitoid Wasps: A Case Study of *Trissolcus* sp. (Hymenoptera: Scelionidae)

Chiao-Jo Tung[1], Yi-Hui Wu[2], Shih-Yang Lee[2], Yan-Fu Kuo[1]
[1]Department of Biomechatronics Engineering, National Taiwan University, Taipei, Taiwan
[2]Biological Control Research Center, Miaoli District Agricultural Research and Extension Station, Ministry of Agriculture

**Written for presentation at the**
**2025 ASABE Annual International Meeting**
**Sponsored by ASABE**
**Toronto, ON, Canada**
**July 13-16, 2025**

**ABSTRACT.** *The use of parasitoid wasps for pest control is an essential strategy in sustainable agriculture. Accurate counting and gender identification are critical for establishing mass production techniques and ensuring product quality, as only female wasps possess parasitism capabilities. Parasitoid wasps are typically tiny, and their sex is often determined by subtle morphological traits. In this study, antennae with distinctly large clava was used to distinguish male and female Trissolcus sp., the target species. Conventional microscopic examination for gender identification is labor-intensive and time-consuming. To address these challenges, this study develops an automated system for counting and sex identification of Trissoclus sp., a parasitoid wasp approximately 1 mm in length that parasitizes Rhynchocoris humeralis, a citrus pest. High-resolution images (6400 dpi) of the wasps were captured using a flatbed scanner. Subsequently, a two-stage deep learning-based approach was implemented for the tasks. In the first stage, the original high-resolution images were downsampled to accelerate the wasp counting. The wasps in the downsampled images were localized and counted using YOLOv7. In the second stage, the bounding boxes of the wasps from YOLOv7 were used to localize and crop the wasps in the original high-resolution images. The cropped wasp images were then used to identify the genders of the wasps using ResNet18. The trained YOLOv7 and ResNet18, respectively, achieved a mean average precision of 98.91% and a validation accuracy of 96.16%. The proposed approach provides a scalable and automated solution for parasitoid wasp identification, streamlining workflows and reducing reliance on manual processes. Future work will focus on improving classification accuracy and enhancing system usability for broader implementation.*

***Keywords.*** *Deep Learning, You Only Look Once (YOLO), Residual Neural Network (ResNet), Biological Control, Parasitoid Wasp*

# Introduction

Parasitoid wasps play a critical role in pest management by naturally controlling agricultural pest populations. However, manual detection and gender classification of these insects present significant practical challenges, particularly for large-scale applications, due to their extremely small size (~1 mm) and, in the case of *Trissolcus* species, the subtle differences of clava were used for sex differentiation (Figure 1). Traditional microscopic methods are labor-intensive, inefficient, and impractical for monitoring large numbers of individuals.


(a) (b) (c)

**Figure 1. (a) Female, (b) Male, and (c) Unrecognizable parasitoid wasps used for classification. All individuals are approximately 1 mm in length. Antennae with distinctly large clava were used as the primary feature for sex identification.**

Recent developments in deep learning have substantially improved insect detection and classification, particularly for complex backgrounds, small targets, and large-scale applications. Liu et al. (2022) introduced GAFPN, enhancing accuracy in detecting small pests. Kumar et al. (2023) used YOLO-based models to improve large-scale insect identification. Additionally, Dewi et al. (2023) applied ResNet models with transfer learning, resulting in better feature extraction, while Hassan & Maji (2024) boosted classification accuracy by incorporating self-attention mechanisms into ResNet architectures.

Despite these advancements, accurately classifying parasitoid wasp gender remains challenging due to their minuscule size and nuanced morphological features. Tuda & Luna-Maldonado (2020) explored traditional machine learning methods like SVM and AdaBoost, which lacked scalability and precision necessary for detailed morphological classification. Similarly, Cannet et al. (2023) applied YOLOv2, MobileNet, and ResNet for phlebotomine sandfly classification, but these models were not specifically optimized for gender differentiation at a micro-scale.

This study aims to develop an automated two-stage deep learning framework combining YOLOv7-based object detection and ResNet18-based gender classification, optimized specifically for high-resolution parasitoid wasp imaging, to facilitate timely and accurate gender identification in field conditions.

# Material and methods

### System Overview

This study develops a two-stage deep learning framework for automating the detection and gender classification process of parasitoid wasps (Fig. 2). The system consists of two integrated modules: a detection module for localizing individual parasitoid wasps and a classification module for identifying wasp gender. First, the detection module uses an object detection model to localize and provide bounding boxes around individual wasps. Then, the classification module analyzes high-resolution cropped images of the wasps to predict their genders.

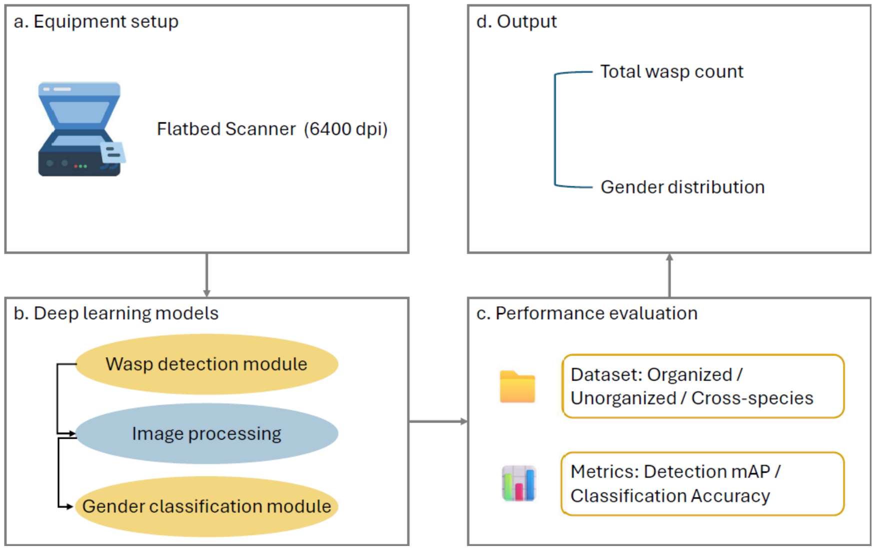



**Figure 2. Flowchart of the proposed system.**

## Image Acquisition and Annotation

Adult parasitoid wasps (*Trissolcus* sp., currently under taxonomic revision) used in this study were reared from egg masses of *Rhynchocoris humeralis* (Thunberg), collected in 2023 from a lemon orchard in Jiaoxi Township, Yilan County, Taiwan. The average body lengths of females and males were 1.045 ± 0.045 mm and 0.969 ± 0.045 mm, respectively (n = 30 per sex).

After natural death, approximately 400 wasps were randomly distributed over a 6 × 6 cm area on the platform of a flatbed scanner (Epson Perfection V850 Pro; Suwa, Japan). The samples were covered with a 9 cm diameter plastic Petri dish lid and overlaid with a white sheet of paper to minimize electrostatic interference and reflective glare during scanning. Images were captured at 6400 dpi using a movable scanning window in the accompanying software to preserve the fine morphological details of the wasps. The scanning window was manually shifted to different regions of the sample resulting in nine distinct images per batch. Each image captured approximately 40 to 50 individual wasps and preserved fine morphological details required for subsequent detection and classification. Due to the tiny nature of the wasps, it was difficult to arrange them neatly, resulting in overlapping between some individuals. An entomology expert at the Miaoli District Agricultural Research and Extension Station (Ministry of Agriculture, Taiwan) annotated the wasps using LabelImg. In total, 150 annotated images were randomly divided into training and test sets with a 4:1 ratio.

## Wasp Detection and Counting

Yolov7 was utilized to detect wasps in the images. To reduce computational cost, the scanner images with original dimensions of 3981 × 3981 pixels (correspondence area of approximately 1.58 × 1.58 cm) were automatically downgraded to 1120 × 1120 pixels. Image augmentation techniques were applied to enhance model robustness during training. The augmentation parameters included hue adjustment (±0.015), saturation adjustment (±0.7), brightness adjustment (±0.4), translation (±20%), scaling (±50%), mosaic (probability = 1.0), and horizontal flipping (probability = 0.5). Model optimization was performed with stochastic gradient descent, the standard optimization algorithm within the YOLOv7 framework. The initial learning rate, momentum, and weight decay were, respectively, set to 0.001, 0.937, and 0.0005. The model was trained for 100 epochs with a batch size of 4. The learning rate was gradually increased during the first three epochs, followed by adjustment through a cosine annealing schedule. After training, wasp detection was performed on each image, and the total number of individuals was obtained by directly counting the number of bounding boxes predicted by the model.

## Gender Classification of Parasitoid Wasps

ResNet18 was employed as the classifier for wasp gender identification. Three categories were used: female, male, and unrecognizable. The areas of wasps in the original image (3981 × 3981 pixels) mapped from the bounding boxes of the wasps detected in the downgraded images by the YOLOv7 were used as the input to ResNet18 (Table 1). The areas were center padded to a fixed size of 640 × 640 pixels without resizing before fed into the ResNet18 model. Data augmentation was applied during training to improve model robustness. The augmentation pipeline included random horizontal and vertical flipping (probability = 0.5), random rotation within ±15°, and color jittering (brightness, contrast, saturation, and hue factors = 0.2). To address class imbalance, class-specific weights were computed and included in the loss function. The model was trained using the AdamW optimizer, with an initial learning rate of 0.00003 and a weight decay of 0.02. Training was conducted over 100 epochs with a batch size of 32, and the learning rate was adjusted throughout the process using a cosine annealing schedule.

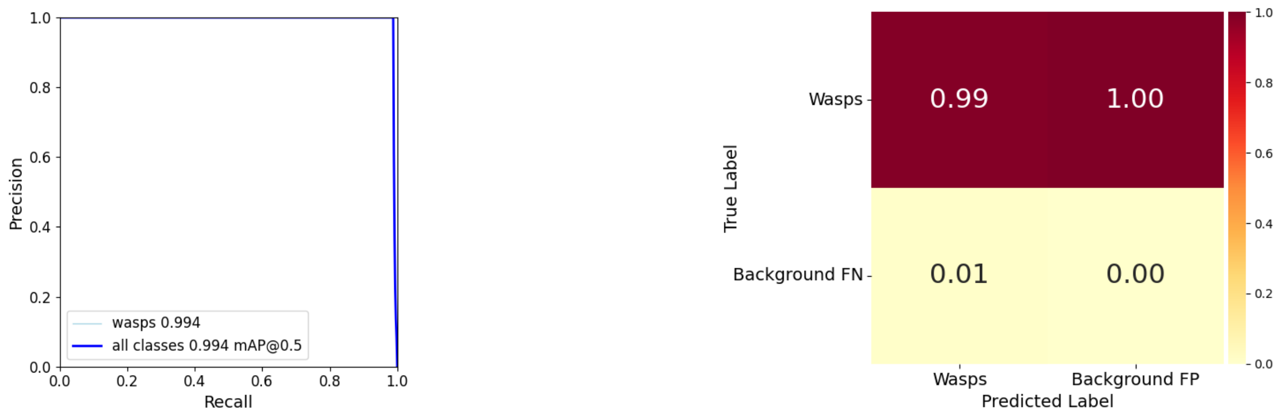
**Table 1. Number of image patches used for training the gender classification model**

| Class | Number of patches |
|---|---|
| Female | 2927 |
| Male | 1166 |
| Unrecognizable | 584 |
| Total | 4677 |

# Results

## Performance of Parasitoid wasp Detection Model

The performance of the YOLOv7 model was evaluated using 26 test images. Inference was performed using a confidence threshold of 0.25 and an IoU threshold of 0.45. The model achieved a precision of 99.9%, a recall of 98.7%, an F1-score of 99.3%, and a mean average precision (mAP) of 99.4%. The corresponding precision-recall curves and confusion matrix are presented in Fig. 3.




(a) (b)

**Figure 3. (a) PR curves of the parasitoid and background classes, and (b) confusion matrix of the trained YOLOv7 model.**

## Performance of Gender Classification Model

The performance of the trained ResNet18 was analyzed using 767 test image patches. The model achieved an overall accuracy of 96.74% (Fig. 4) and a mean average precision of 95.86% (Table 2).

**Table 2. Number of image patches used for model training and internal validation across the three classes**

| Category | Precision (%) | Recall (%) | F1-score (%) |
|---|---|---|---|
| Female | 99.3 | 95.8 | 97.5 |
| Male | 96.5 | 98.9 | 97.7 |
| Unrecognizable | 91.8 | 92.6 | 92.2 |
| Overall | 95.86 | 95.76 | 95.8 |

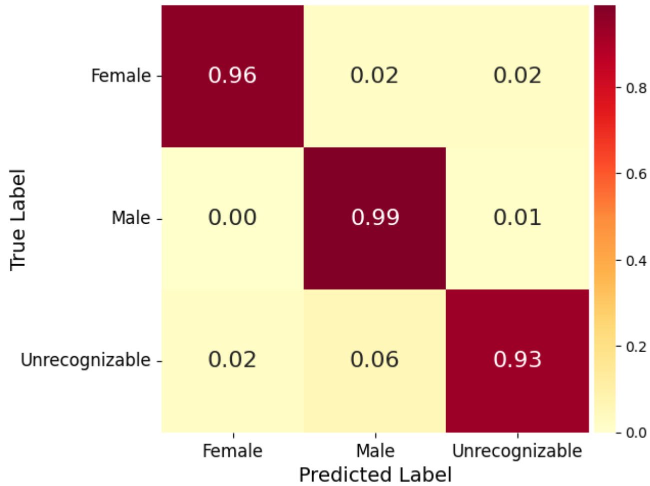



**Figure 4. Normalized confusion matrix of ResNet-18 model predictions for parasitoid wasp gender classification.**

# Discussion

### Impact of Dataset Complexity

To examine the robustness of the trained YOLOv7 model under challenging visual conditions, performance was tested on an unorganized dataset comprising of 886 parasitoid wasps extracted from 26 test images. In contrast to the organized test dataset used in the initial evaluation, the unorganized dataset contained densely packed individuals with frequent overlaps, increasing the difficulty of both detection and gender classification. This dataset included 326 females, 379 males, and 181 unrecognizable individuals.

Under these conditions, the YOLOv7 detection model continued to demonstrate strong performance, achieving a mean average precision (mAP) of 99.7%, indicating that object localization was minimally affected by overlapping individuals. Based on these detection outputs, the ResNet18 classifier yielded an overall classification accuracy of 92.89%, with the per-class average precision, recall, and F1-score of 91.44%, 92.57%, and 91.90%, respectively (Table 3).

**Table 3. Per-class precision, recall, and F1-score on unorganized dataset**

| Dataset | Class | Precision (%) | Recall (%) | F1-score (%) |
|---|---|---|---|---|
| Unorganized | Female | 95.47 | 90.49 | 92.91 |
| | Male | 96.28 | 95.51 | 95.89 |
| | Unrecognizable | 82.58 | 91.71 | 86.91 |
| | Overall | 91.44 | 92.57 | 91.90 |

### Cross-Species Validation

To explore the applicability of the trained model, we conducted a cross-species validation using a supplementary dataset of *Trissolcus mitsukurii*, a morphologically distinct species that, in this study, was also classified based on antennae with distinctly large clava. A total of 811 individuals were obtained from 19 high-resolution images, consisting of 310 females, 404 males, and 97 unrecognizable individuals. Although *T. mitsukurii* differs from the original *Trissolcus* population in facial morphology—particularly in the presence of an interocular groove—both species use the relative size of the antennal clava as the primary feature for distinguishing between sexes.

Although *T. mitsukurii* differs from the original *Trissolcus* population in facial morphology—particularly in the presence of an interocular groove—the YOLOv7 detection model maintained high detection accuracy, reporting a mean average precision (mAP) of 99.8%. The ResNet18 classifier attained an overall classification accuracy of 92.23%. The average precision, recall, and F1-score across the three target classes were 87.99%, 89.74%, and 88.73% (Table 4). These results demonstrate that the proposed framework remains effective even when moderate interspecific morphological differences are introduced, supporting its potential use in related parasitoid wasp analysis under shared classification standards.

**Table 4. ResNet18 classification results on the *T. mitsukurii* dataset**

| Dataset | Class | Precision (%) | Recall (%) | F1-score (%) |
|---|---|---|---|---|
| T. *mitsukurii* | Female | 97.60 | 91.94 | 94.69 |
| | Male | 93.64 | 94.80 | 94.22 |
| | Unrecognizable | 72.73 | 82.47 | 77.29 |
| | Overall | 87.99 | 89.74 | 88.73 |

# Conclusion

This study developed a two-stage deep learning framework for automated sex identification of parasitoid wasps (*Trissolcus* sp.). The framework integrated YOLOv7 for wasp detection and ResNet18 for gender classification. The trained YOLOv7 and ResNet18 models achieved a mAP of 99.4% and a classification accuracy of 96.74%, respectively. Additional evaluations using datasets containing overlapping individuals and a related species (*Trissolcus mitsukurii*) demonstrated that the framework remains robust under visual occlusion and cross-species variation. The proposed method provides a scalable and effective solution for enhancing parasitoid wasp production and supporting sustainable agricultural pest management.

# References

Tuda, M., & Luna-Maldonado, A. I. (2020). Image-based insect species and gender classification by trained supervised machine learning algorithms. *Ecological Informatics* 60: *101135*.

Cannet, A., Simon-Chane, C., Histace, A., Akhoundi, M., Romain, O., Souchaud, M., & Sereno, D. (2023). Species identification of phlebotomine sandflies using deep learning and wing interferential pattern (WIP). *Scientific Reports* 13(1): 21389.

Liu, L., Wang, R., Xie, C., Li, R., Wang, F., & Qi, L. (2022). A global activated feature pyramid network for tiny pest detection in the wild. *Machine Vision and Applications* 33(5): 76.

Kumar, N., Nagarathna, & Flammini, F. (2023). YOLO-based light-weight deep learning models for insect detection system with field adaption. *Agriculture* 13(3): *741*.

Dewi, C., Christanto, H. J., & Dai, G. W. (2023). Automated identification of insect pests: A deep transfer learning approach using ResNet. *Acadlore Trans. Mach. Learn* 2(4): 194-203.

Hassan, S. M., & Maji, A. K. (2024). Pest Identification based on fusion of Self-Attention with ResNet. *IEEE Access*.