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Araştırma Makalesi

Detection of the *Metcalfa pruinosa* (Hemiptera: Flatidae) pest on the Jujube plant (*Ziziphus jujuba*) using a sequence of YOLOv5 models

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ABSTRACT

This study aimed to detect the adult of the pest *Metcalfa pruinosa* observed on jujube plants using the YOLOv5 algorithm's v5s, v5m, and v5l models. Thus, it serves as a resource for the devices used to determine the initiation of agricultural pest control and for robotic systems that perform spraying based on pest population density. After obtaining the images to be used for training the models, the datasets were augmented using data augmentation methods and labeled using Roboflow. Subsequently, the models were trained using these datasets, and the performance metrics such as box_loss, obj_loss, precision, recall, mAP_0.5, and mAP_0.5:0.95 of the trained models were analyzed. In the YOLOv5s model, the box_loss and obj_loss performance metrics were found to be the highest, with values of 0.02858 and 0.0055256, respectively. In the YOLOv5m model, the recall performance metric was identified as the highest, with a value of 0.98127. In the YOLOv5l model, precision, mAP_0.5, and mAP_0.5:0.95 performance metrics were identified as the highest, with values of 0.98122, 0.99500, and 0.67864, respectively. Consequently, the YOLOv5l model exhibits higher precision compared to others. It is believed that the YOLOv5l model is sufficient for the detection of the *Metcalfa pruinosa* pest.

Key words: Precision agriculture, image processing, pest detection, convolutional neural network

Hünnap Bitkisinde (*Ziziphus jujuba*) *Metcalfa pruinosa* (Hemiptera: Flatidae) Zararlısının YOLOv5 Model Serisi ile Tespiti

ÖZ

Bu çalışma, hünnap bitkilerinde gözlemlenen *Metcalfa pruinosa* zararlısının erginlerini tespit etmek amacıyla YOLOv5 algoritmasının v5s, v5m ve v5l modellerini kullanmayı hedeflemiştir. Böylelikle, tarımsal mücadelenin başlama anını belirlemek için kullanılan cihazlar ve zararlı popülasyon yoğunluğuna göre ilaçlama yapan robotik sistemler için bir kaynak teşkil etmektedir. Modellerin eğitimi için kullanılacak görüntüler elde edildikten sonra, veri artırımı yöntemleri kullanılarak veri setleri genişletilmiş ve görüntüler Roboflow kullanılarak etiketlenmiştir. Ardından, bu veriler kullanılarak modeller eğitilmiş ve eğitilen modellerin box_loss, obj_loss, precision, recall, mAP_0.5 ve mAP_0.5:0.95 gibi performans metrikleri analiz edilmiştir. YOLOv5s modelinde, box_loss ve obj_loss performans metriklerinin sırasıyla 0.02858 ve 0.0055256 değerleri ile en yüksek olduğu bulunmuştur. YOLOv5m modelinde, recall performans metriğinin 0.98127 değeri ile en yüksek olduğu tespit edilmiştir. YOLOv5l modelinde ise precision, mAP_0.5 ve mAP_0.5:0.95 performans metriklerinin sırasıyla 0.98122, 0.99500 ve 0.67864 değerleri ile en yüksek olduğu belirlenmiştir. Sonuç olarak, YOLOv5l modeli diğerlerine göre daha yüksek doğruluk sergilemektedir. YOLOv5l modelinin, *Metcalfa pruinosa* zararlısının tespiti için yeterli olduğu düşünülmektedir.

Anahtar kelimeler: Hassas tarım, görüntü işleme, zararlı tespiti, evrişimli sinir ağları

INTRODUCTION

Ziziphus jujuba, commonly referred to be Jujube and scientifically classified within the Rhamnaceae family, denotes a fruit tree species. Originating primarily in Asian regions such as China, Korea, Japan, and India, it has attained global cultivation (Mengjun, 2003; Ivanišová et al., 2017). *Z. jujuba* trees are typified by their spiny branches and dense green foliage, attaining heights typically ranging from 5 to 12 meters. The fruits they bear are small and oval-shaped, transitioning to a reddish-brown hue upon ripening. Renowned for its sweet-tangy flavor profile, Jujube fruit finds consumption in both dried and fresh forms (Mahajan and Chopda, 2009; Grygorieva et al., 2014; Kavas and Dalkılıç, 2015; Hürkan, 2019)

This plant is extensively utilized in the food industry, incorporated into a variety of products such as confectioneries, preserves, teas, and syrups. Moreover, it holds considerable significance in traditional Chinese medicine. *Z. jujuba* distinguishes itself through its constituent elements, which encompass polysaccharides, flavonoids, triterpenes, and phytochemical compounds (Li et al., 2007; Choi et al., 2011). Consequently, *Z. jujuba* emerges as a vital reservoir catering to both gastronomic and therapeutic requisites (Ji et al., 2021).

In recent years, the Citrus Flatid Planthopper, scientifically recognized as *Metcalfa pruinosa* (Hemiptera: Flatidae), has emerged as a destructive force impacting *Z. jujuba* trees. This species constitutes an invasive pest (Szelényi et al., 2024). Adult Citrus Flatid Planthoppers typically measure 6 to 8 millimeters in length, presenting a light yellow hue. Their bodies are enveloped in a white waxy filament, imparting a cotton-like appearance (Gnezdilov and Sugonyaev, 2009; Kim et al., 2011; Preda and Skolka, 2011; Kim et al., 2020). These deleterious insects sustain themselves by extracting plant sap from their host plants. Their feeding activities on Jujube trees and other susceptible plants can lead to symptoms such as leaf yellowing, browning, and distortion, thereby detrimentally affecting plant growth and productivity (Ciceoi et al., 2017; Stănică, 2019). The proliferation and expansion of Citrus Flatid Planthopper populations can induce significant agricultural losses, particularly in citrus orchards and other agricultural domains. They have the potential to compromise fruit quality, impede plant development, and precipitate yield reductions (Strauss, 2010; Byeon et al., 2018).

Metcalfa pruinosa is a widely polyphagous invasive insect species in Europe known for its ability to transmit phytoplasma (Szelényi et al., 2024). This pest, commonly found on jujube trees, tends to blend into its natural environment in a highly camouflaged manner. *M. pruinosa* constitutes a detrimental insect species posing a significant threat to the agricultural sector. Hence, comprehending the damages inflicted by these pests on afflicted plants, monitoring their dispersal, and investigating efficacious control measures are paramount for upholding sustainability and productivity within the agricultural domain (Preda and Skolka, 2011; Lee et al., 2019; Erdoğan et al., 2023).

Image processing entails the manipulation of digital photographs using computer software for specific purposes. These techniques are commonly applied to images acquired through cameras or scanners, with pertinent features extracted via image preprocessing procedures. Image processing methodologies find diverse applications across fields, such as background removal and object recognition. Among the commonly utilized techniques are color determination, shape analysis, edge manipulation, pattern recognition, and matching. Convolutional Neural Networks (CNNs) present advanced approaches to image analysis, particularly in the realm of diagnosing plant pests (Nguyen et al., 2019; Liu and Wang, 2020). CNN-based models, such as the YOLO (You Only Look Once) algorithms, exhibit superior performance in speed and accuracy. These models are pivotal in efficiently analyzing images to detect plant diseases and pests (Kang et al., 2023). The present study employed a series of YOLOv5 algorithms for these capabilities. The YOLOv5 series is a deep learning-based object detection model designed to address the object detection problem, mainly intended for real-time applications. YOLO represents an approach that processes the image in a single pass using a single deep neural network, classifying objects simultaneously. The YOLOv5 family comprises enhanced versions of the original YOLO architecture and has been introduced in different sizes (small, medium, and large). The fundamental differences between YOLOv5s, YOLOv5m, and YOLOv5l stem from the size and complexity of the model's architectural structure and parameters. YOLOv5s features a smaller architecture, whereas YOLOv5l possesses a larger and more complex structure. These differences may lead to variations in performance metrics such as processing speed, detection accuracy, and computational intensity. Larger models generally have the capability to detect more complex objects at higher resolutions, whereas smaller models can operate faster and require less computational power. However, larger models demand more computational power and memory during both training and inference processes due to their increased number of parameters. Additionally, while larger models may have a greater capacity for learning from data, smaller models often exhibit faster learning and training processes. Therefore, the choice between YOLOv5s, YOLOv5m, and YOLOv5l models may depend on the specific requirements and use cases of a particular application. YOLOv5s might be preferred for real-time applications requiring faster processing, whereas YOLOv5l could be favored for applications demanding higher accuracy. The selection of these models necessitates a balance between factors such as computational power, memory requirements, and detection performance, typically tailored to best fit the specific requirements of the application.

The advantages and disadvantages of each model can vary depending on the usage scenario. Smaller models typically provide quick solutions, whereas larger models may offer higher precision and better detection performance. The selection should be made based on application requirements and hardware limitations. These models are often chosen to suit different application scenarios. The various sizes of YOLOv5 models are presented in Table 1.

Table 1. Comparison of YOLOv5 models with default parameters (www.github.com/ultralytics/yolov5)

Model	Size (pixels)	mAP^{val} (50-95)	mAP^{val} (50)	Speed CPU b1 (ms)	Speed V100 b1 (ms)	Speed V100 b32 (ms)	Parameters (M)	FLOPs @640 (B)
YOLOv5n	640	28.0	45.7	45	6.3	0.6	1.9	4.5
YOLOv5s	640	37.4	56.8	98	6.4	0.9	7.2	16.5
YOLOv5m	640	45.4	64.1	224	8.2	1.7	21.2	49.0
YOLOv5l	640	49.0	67.3	430	10.1	2.7	46.5	109.1
YOLOv5x	640	50.7	68.9	766	12.1	4.8	86.7	205.7

Numerous studies exist on plant disease and pest detection utilizing YOLO. For instance, Omer et al. (2023) conducted a study on disease and pest detection in cucumber plants using the enhanced YOLOv5l model. Xu et al. (2023) tested the invasion level of the *Aphis gossypii* Glover pest on cotton seedlings using three different models (Faster Region-based Convolutional Neural Network (R-CNN), YOLOv5, and single-shot detector (SSD) models). Li et al. (2022) employed the YOLO-JD model for disease and pest detection in Jute (*Corchorus olitorius* L. or *C. capsularis* L.) plants. Wen et al. (2022) conducted studies on almost all versions of the YOLO model for 24 different plant pests and developed a model called Pest-YOLO. Sorbelli et al. (2023) performed detection of *Halyomorpha halys* using a YOLO-based model. YOLO algorithms significantly contribute to the success in plant disease and pest detection. No study has been encountered regarding the detection of the pest Metcalfa pruinosa using image processing techniques, thus suggesting the novelty of such investigation. This study aims to detect *M. pruinosa* adult pests using the YOLO-v5 model series algorithm on Jujube plants through field images.

MATERIALS and METHODS

Image Annotation and Dataset Production

This paper uses the Roboflow labeling tool to label the dataset. The text documents containing the coordinates and class information of the objects to be used for training the deep learning model were obtained. The pest images were obtained using an iPhone 7. The images constituting the dataset have a resolution of 768x1024 pixels, 96 dpi, and a color depth of 24 bits. The objects to be labeled are clearly discernible to the human eye. When the images are reduced to the input size of the models, this clarity is not lost. Imaging can be performed at any time of day when there is daylight. Image augmentation techniques (Figure 1) such as horizontal flip, vertical flip, clockwise 90° rotation, counterclockwise 90° rotation, shear (± 10° horizontal and vertical), and blur were applied to augment the images. These operations can enhance the model's generalization ability by enabling it to better recognize objects under various conditions. Additionally, increasing the variance in the dataset can reduce overfitting. Consequently, it can lead to improved performance of the model on real-world images. The images were obtained from jujube trees cultivated in Bursa-Türkiye region with coordinates (40°13'20.1"N 28°55'40.1"E).

Figure 1. Augmentation techniques (from left to right for each row; original image, clockwise 90° rotation, counterclockwise 90° rotation, blur, horizontal flip, vertical flip, horizontal shear, vertical shear, respectively)

In this study, the same dataset consisting of training, validation, and test contents was used to create the three mentioned YOLO versions using the parameters listed in Table 2. The dataset used for each deep learning model (YOLOv5s, YOLOv5m, YOLOv5l) was kept consistent to enable an objective evaluation of the models' performance. Since using augmented data during the testing phase would not be an appropriate approach to assess the model's real-world performance accurately, only original photos were used for the test set. In contrast, the training and validation sets were expanded using data augmentation methods.

Table 2. Distribution of the dataset

Dataset	Number of Original Images	Number of Augmented Images
Train	105	735
Validation	30	210
Test	15	-

Model Training

Numerous parameters are provided to the algorithm during the training of YOLO models. These parameters can be adjusted by extending the training duration, modifying the optimization model, and adding or removing augmentation techniques, depending on how well the model can generalize the detected object. While training with more iterations does not always guarantee the creation of a more precise and accurate model capable of better generalization, the 'patience' parameter can halt the training process of a model that is still learning. The utilization of augmentation techniques related to the HSV color space for a model intended to make predictions in the gray channel may adversely affect the training process. In this study, the augmentation techniques depicted in Figure 1 and the training parameters presented in Table 3 were employed. The models were trained using Google Colab, and the parameters mentioned in the table were adjusted in this environment. Regarding the system used, the NVIDIA Tesla T4 GPU is employed in Google Colab, characterized by its capability to efficiently handle deep learning tasks with its CUDA cores and high memory bandwidth. Its specifications include a power consumption of 70W, a maximum memory capacity of 15360MiB, and support for CUDA version 12.2.

Table 3. Training parameters

Training Parameters	**Value**
Epoch	1000
Batch Size	16
Image Size	640x640
Patience	350

Each trained model is evaluated using the metrics shown in Table 4. These metrics indicate how well the model can generalize the object it is intended to detect.

Table 4. Metrics of performance of the models

Metrics	**Formulation**	**Description**
Mean Average Precision (mAP)	$mAP = \frac{1}{C}\sum_{i=1}^{C} AP_i$	mAP is a metric that measures the performance of an object detection model, representing the average precision calculated for each class. N: total number of classes APi: Represents the area under the Precision-Recall curve for the i-th class.
Recall (Classification Sensitivity)	$R = \frac{TP}{TP + FN}$	It is the ratio of true positive objects to the sum of total true positives and false negatives. High 'Recall' indicates the model's ability not to miss objects. TP: True positive, FN: False negative
Precision	$P = \frac{TP}{TP + FP}$	It is the ratio of true positive objects to the sum of total true positives and false positives. FP: False positive
TP		True positive represents the scenario where the model correctly detects an object.
FP		False positive represents the scenario where the model erroneously detects an object that is not actually present.
TN		True negative represents the scenario where the model correctly does not detect an object that is not actually present.
FN		False negative represents the scenario where the model fails to detect an object that is present.

RESULTS AND DISCUSSIONS

The YOLO-v5 model series has newer release dates and features the ability to automatically stop the training process early, rather than using a manual 'patience' parameter. This prevents the 5s, 5m, and 5l models examined in our study from being trained with the same number of epochs. Therefore, to test whether the YOLO algorithm can generalize the pest adequately, we examined the v5 model series, which takes this parameter manually. The YOLO-v4 algorithm, an older release than YOLOv5, is based on the CSPDarknet53 architecture, making the training process more complex. While YOLO-v4 was developed by Alexey Bochkovskiy, YOLO-v5 was developed by a company named Ultralytics. The developed model architecture is based on Pytorch, making the training process more user-friendly. The training and fine-tuning processes are simpler and more flexible. Artificial intelligence algorithms, surpassing human selectivity, have demonstrated notable success. Among the robotic systems utilized in nearly all agricultural operations, the primary concern is to minimize pesticide usage. Targeted spraying against diseases and pests has become more prevalent, focusing on specific plant parts rather than widespread application (Bütüner et al., 2023; Erdoğan et al., 2023; Şahin et al., 2023a; Şahin et al., 2023b; Bütüner et al., 2024). The concept of big data plays a crucial role in the success of these systems. Data stands as the foremost input for artificial intelligence.

Analysis of Training YOLOv5s, v5m, v5l Results

When comparing the metrics of YOLOv5 models (Table 5), it is evident that the YOLOv5l model exhibits some significant differences compared to the others:

- Box_loss value: Box_loss measures how close the predicted bounding box of an object is to the actual bounding box. A low box_loss value indicates that the model is framing objects more accurately. The YOLOv5l model has a 1.93% lower box_loss value than YOLOv5m and %34.67 lower than YOLOv5s.
- Obj_loss value: Obj_loss measures the model's ability to correctly classify whether an object is present or not. A low obj_loss value indicates that the model is classifying objects correctly. The YOLOv5l model has a 18,78% lower obj_loss value than YOLOv5m and 19.38% lower than YOLOv5s.
- Precision: Precision measures how accurately the model detects truly existing objects. High precision means the model is reducing the number of false positive detections. The YOLOv5l model has a 0.13% higher precision value than YOLOv5m and 1.21% higher than YOLOv5s.
- Recall: Recall measures how many of the truly existing objects are correctly detected by the model. High recall means the model is reducing the number of false negative detections. The YOLOv5m model has a 0.20% higher recall value than YOLOv5m and 1.60% higher than YOLOv5s.
- mAP_0.5 value: mAP (Mean Average Precision) is a commonly used metric in object detection. The 0.5 threshold value indicates the scenario where the object bounding box overlaps by 50%. Each model has a same value.
- mAP_0.5:0.95 value: This is another type of mAP calculated by averaging precision values with different threshold values during object detection. The 0.5:0.95 range indicates threshold values ranging from 50% to 95%. The YOLOv5l model has a 9.84% higher mAP_0.5:0.95 value than YOLOv5m and 21.18% higher than YOLOv5s.

These differences indicate that the YOLOv5l model generally exhibits better performance. Lower losses and higher precision and accuracy values suggest that this model has better object detection capabilities.

Table 5. Metrics of performance of the models

Metrics	YOLOv5s	YOLOv5m	YOLOv5l
box_loss	0.028758	0.019156	0.018786
obj_loss	0.0055256	0.0054848	0.0044546
cls_loss	-	-	-
precision	0.96949	0.97996	0.98122
recall	0.96582	0.98127	0.97928
mAP_0.5	0.995	0.995	0.99500
mAP_0.5:0.95	0.56	0.6178	0.67864

When examining the training and validation graphs (Figure 2, 3 and 4) of the models, it was observed that the loss functions generally followed a decreasing trend, with training losses and validation losses decreasing in parallel. The continued decrease in validation loss throughout the training process indicates that no overfitting occurred.

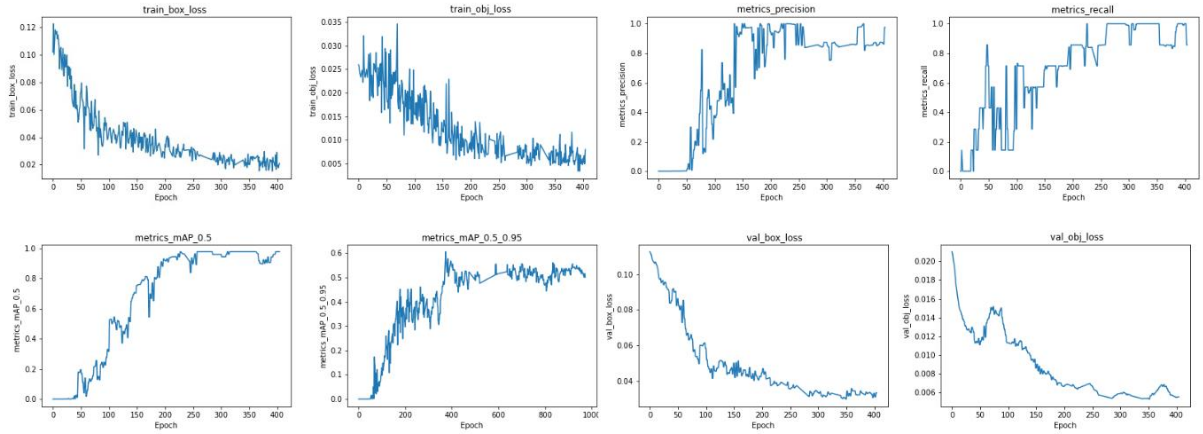

Figure 2. Training results of YOLOv5s

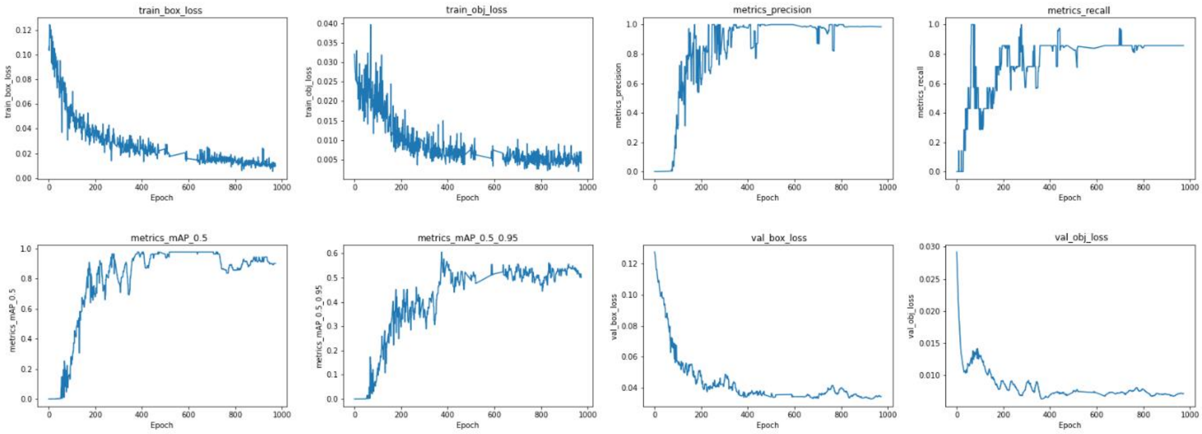

Figure 3. Training results of YOLOv5m

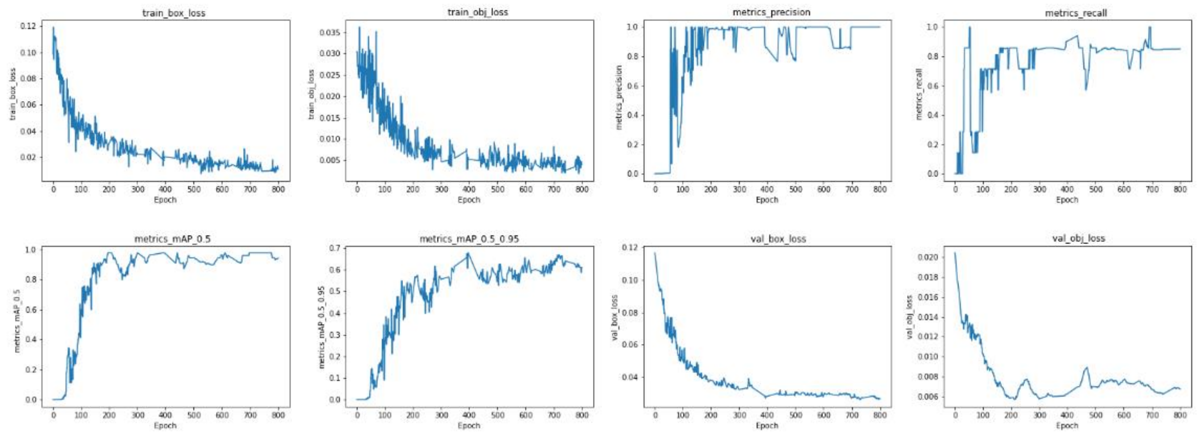

Figure 4. Training results of YOLOv5l

These differences indicate that the YOLOv5l model generally exhibits better performance. Lower losses and higher precision and accuracy values suggest that this model has better object detection capabilities. In plant disease and pest detection, all versions of the YOLO algorithm are effectively utilized. Detailed studies on detecting *Metcalfa pruinosa* pest through image processing are scarce; therefore, this study is deemed to contribute to the literature. Ahmad et al. (2022) conducted a study where they used all versions of YOLOv3, YOLO-Lite, YOLOR, and YOLOv5 to detect 23 different insects. While they did not have any findings related to *Metcalfa pruinosa*, they obtained data on the more precise and faster detection of YOLOv5 compared to other algorithms. Our study yields similar results in this regard. Domingues et al. (2022) detected certain pests (such as bemisia tabaci, helicoverpa armigera) using sticky traps with YOLOv5, reaching a 94.4% mAP_0.5, with a precision and recall of 88% and 91%, respectively, using YOLOv5x. In their experiment, Zhang et al. (2023) observed six diverse pests, including *tobacco whiteflies*, *leaf miners*, *aphids*, *fruit flies*, *thrips*, and *houseflies*. They achieved an average recognition accuracy of 96% using the YOLOv5 model. Wang et al. (2023) employed a YOLOv5-based algorithm to detect diseases (*Leaf blight*) and pests (*Apolygus lucorum*) in tea leaves and obtained positive results. Yang et al. (2023) examined nine different diseases and pests in rice plants using a YOLOv5-based algorithm. Their results increased the mAP value to 94.4%

Detection Results on Test Images

In Figure 5, the results of three different test images are presented. Detecting Metcalfa pruinosa in RGB imaging is particularly challenging, as depicted in the figure. Despite the difficulty in verifying ground truth, this pest has been successfully detected using YOLOv5s, 5m, and 5l models. However, the success rate with YOLOv5l is slightly higher compared to the others.

Figure 5. Results of YOLOv5 versions: **a** original test images, **b** YOLOv5s results, **c** YOLOv5m results, **d** YOLOv5l results

CONCLUSION

In conclusion, a study was conducted on the detection of the pest Metcalfa pruinosa using different models of the YOLOv5 algorithm. It was observed that the YOLOv5l model outperformed the others in detection. There is potential for improving the algorithm's precision, recall, mAP_0.5, and mAP_0.5:0.95 values. Based on the available data, it has been determined that the YOLOv5 algorithm can be used for the detection of this pest in its adult stage.

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