# Automated Recognition Model for Identifying Harmful and Harmless Insects in Crop Management

**Amal Alshahrani[1], Rana Alsaedi[2], Ameera Alfadli[2], Taif Alahmadi[2], Deema Alqthami[2] and Ohoud Alzubaidi[2]**

[1,2]Department of Computer Science and Artificial Intelligence, College of Computing, Umm

## Abstract

Agriculture is often affected by the spread of diseases and pests, which can cause significant economic losses. Worldwide, pests can cause yield losses of up to 40%. To minimize these losses, it is crucial to detect and identify pests as early as possible. Prior studies have developed detection models to either detect harmful insects or only harmless insects. However, there has been no model developed to detect both categories together. To address this issue, we aim to develop a model that can detect and classify both harmful and harmless insects in agricultural environments. We will assess the accuracy of three different methods: YOLO (You Only Look Once) versions 8 and 9, and VGG16 (Visual Geometry Group) on a dataset comprising ten classes, five for harmful insects and five for harmless insects, to determine the most effective approach. The results indicate that YOLOv9 achieved the highest accuracy of 0.972, followed closely by YOLOv8 with 0.969, while VGG16 lagged at 0.849. This suggests that YOLOv9 is the most effective tool among the tested models for detecting and classifying both harmful and harmless insects in agricultural settings.

***Keywords:***

*YOLO, VGG-16, Insects, harmful, harmless*

## 1. Introduction

In agricultural fields, insects can play both positive and negative roles. Some insects, like bees and butterflies, help pollinate crops, while others, such as the gypsy moth, codling moth, and diamondback moth, can cause significant damage to crops worldwide. These insects lay numerous eggs, and their larvae feed heavily, leading to direct defoliation, which can result in substantial crop yield losses [1]. It's important to be able to identify these insects accurately for effective farm management and to maintain a healthy ecosystem. In the past, farmers and entomologists had to rely on manual identification, which was time-consuming and often prone to errors due to the large number of insect species.

The world of Artificial Intelligence (AI) has made significant advancements in machine learning technologies, which have transformed the way we solve problems. One of the major challenges in the field of pest detection has been addressed by the use of image recognition powered by advanced convolutional neural networks (CNNs). This paper aims to compare three state-of-the-art AI models–YOLOv8, YOLOv9, and VGG16–that offer automated insect classification. Each model has a unique approach to image processing and learning capabilities, making them ideal candidates for a thorough comparative analysis.

YOLO is a state-of-the-art object detection algorithm that is currently the most advanced of its kind. This revolutionary CNN excels at identifying objects with remarkable accuracy and speed in real-time [2]. VGG16 is a well-known convolutional neural network utilized for object classification and image recognition. This model effectively interprets intricate image features through its 16 convolutional and fully connected layers [3].

This research aims to address the increasing demand from the agricultural industry for technologies that enhance crop yields while promoting sustainable farming practices. Specifically, the study evaluates the performance of three AI models in recognizing different insect species. The goal is to identify the most effective model for practical deployment in fields worldwide. The research problem involves assessing the accuracy of these models in real-world conditions, which is both crucial and challenging.

This paper provides insights and clarity on how AI can be applied to insect detection in agriculture. The paper starts with an extensive review of existing research on the subject, which includes the evolution of technologies and their adoption in agriculture. The paper then discusses the data collection method. The research methodology is then outlined, covering the dataset used and model training. In

Manuscript received May 5, 2025
Manuscript revised May 20, 2025
https://doi.org/10.22937/IJCSNS.2025.25.5.8

the results and discussion section, a detailed analysis of each model's performance is presented. Finally, the paper concludes with recommendations for future research directions and potential enhancements in AI-driven pest management solutions.

## 2. Literature Review

In this section, we will review the literature related to detection models for identifying harmful or harmless insects. The research has been arranged from newest to oldest, starting from 2023 to 2018.

Firstly, in the study "Optimisation of Residual Network Using Data Augmentation and Ensemble Deep Learning for Butterfly Image Classification" by Diniati Ruaika et al. [4], the authors aim to enhance the accuracy of the ResNet50 model by employing data augmentation and ensemble deep learning techniques specifically for butterfly image classification. Utilizing a public dataset from Kaggle, which includes 75 distinct butterfly species, the researchers integrated ResNet50 with a CNN to develop an ensemble deep-learning model. The effectiveness of the ResNet50 optimization was evaluated by comparing the experimental results from the original dataset with those obtained through the proposed methods, using various evaluation metrics. The study concluded that the proposed approach significantly improved performance, achieving an accuracy of 95%.

Moving on, Kumar et al. [5] focused on developing YOLO-based deep learning models for accurate insect detection and classification, particularly targeting insect pests. The study involved collecting a public insect image dataset, annotating and augmenting the data, and training the YOLOv5 object recognition model. The YOLOv5x model achieved a mean average precision (mAP) of 93% and an F1 score close to 0.90, outperforming other YOLOv5-based models. The authors suggested future improvements, including combining MobileNet with YOLOv5x to enhance detection speed and optimize the system for real-time applications in computational entomology.

Furthermore, in a paper by Sorbelli et al. [6], use of innovative technologies such as RGB cameras, drones, and computer vision algorithms to monitor pests in orchards, specifically Heliomorpha hallis (HH), also known as the “ornate brown stink bug.” Vision models were trained on high-quality images from a public dataset. Images captured by a drone were analyzed, taking into account factors such as noise and brightness, to improve the performance of machine learning algorithms. The results of the paper indicate that the machine learning models demonstrated satisfactory performance in identifying HH, with the YOLO framework proving particularly effective.

Moreover, in a study conducted by Stark et al. [7], AI algorithms were developed to recognize flower-visiting arthropods, which have the potential to revolutionize pollinator monitoring. The study used a methodology that involved training YOLO models such as YOLOv5nano, YOLOv5small, and YOLOv7tiny on over 17,000 annotated images. The models were tested on eight groups of flower-visiting arthropods. The results demonstrated that all three YOLO models achieved high accuracy, ranging from 93% to 97%. The study also highlighted the need for further research to improve the models' performance in scenarios where images have multiple overlapping individuals, varying lighting conditions, and different arthropod species with similar appearances.

Meanwhile, in a study conducted by Anwar and Masood [8], an ensemble-based model was developed using transfer learning, and experiments were conducted with pre-trained models such as VGG16, VGG19, and ResNetv50. An accuracy of 82.5% was achieved, representing a significant improvement over recent state-of-the-art models. The paper suggested using object detection algorithms like YOLO and Faster RCNN, as well as exploring other optimization techniques, parameters, and CNN models to improve performance due to the dataset's large number of classes and variable sample distribution.

Furthermore, The study conducted by Wen et al. [9] The study presents Pest-YOLO, a model that utilizes RGB cameras, drones, and computer vision to detect dense and small agricultural pests. The work addresses the issue of effectively monitoring crop pests by enhancing previous methods with a modified YOLO framework. This framework incorporates an improved loss function and a unique bounding box selection algorithm. When evaluated on the comprehensive Pest24 dataset, Pest-YOLO surpasses other models, reaching a mean average precision of 69.59% and a mean recall of 77.71%. This demonstrates its exceptional capacity in practical agricultural environments, offering significant progress in automated pest control. Further study is needed to enhance the model's versatility and its precision in detection.

Additionally, Thenmozhi Kasinathan et al. [10] explored automating crop pest detection using machine learning. Traditional methods required trained taxonomists, but the study applied artificial neural networks (ANN), support vector machines (SVM), k-nearest neighbors (KNN), naive bayes (NB), and convolutional neural network (CNN) models to classify insects. Results showed

CNN achieving the highest accuracy of 91.5% and 90% for nine and 24-class datasets, respectively. An insect pest detection algorithm, utilizing image processing, accurately identified insects amidst complex backgrounds in field crops. The study underscored the significance of efficient pest detection to mitigate crop damage and enhance productivity, with future research aiming to integrate the algorithm into deep Convolutional Neural Network (CNN) models for larger datasets.

In the same context, Marković et al. [11] introduced a novel approach for predicting pest insect appearance utilizing sensors and machine learning algorithms. Their model aimed to aid farmers in the timely detection and control of pest insects, thus mitigating yield loss. By analyzing environmental parameters like temperature and relative humidity, the model predicted insect occurrences on a daily basis. They employed various machine learning algorithms, achieving up to 86.3% accuracy in predicting insect appearance over five days. The study highlighted the importance of early detection for effective pest management in agriculture, demonstrating the potential of machine learning in precision agriculture applications.

Additionally, in a study by Homchan et al. [12], a machine learning model was developed using the Google Teachable Machine (GTM) tool to classify two economically important cricket species, Acheta domesticus and Gryllus bimaculatus, and determine their sex. The experimental investigation used pre-processed still images extracted from high-resolution videos. The training dataset comprised 2247 images, while 399 images were used to test the trained model. The results show that the trained ML model achieved a prediction accuracy of 100%. Future improvements may include expanding the model to encompass a broader range of insect species and enhancing the ML-driven system for automated and online applications.

Furthermore, AI et al. [13] explored how to use technology to automate the recognition of crop diseases. They used a model called Inception-ResNet-v2 to train a computer program to identify 27 types of disease in 10 different crops. The images used in the study were from the AI Challenger Competition held in 2018. The results showed that the computer program was able to recognize crop diseases with an 86.1% accuracy rate, proving that it was effective. The researchers also created a WeChat applet, which farmers can use to identify crop diseases and pests in real time. The computer program showed better accuracy and performance compared to traditional deep learning models and could even identify specific ailments like corn leaf rust. This makes it a useful tool for pest management in agriculture. The researchers suggested that this hybrid network model is a promising way to detect plant diseases and insect pests more effectively than traditional models. Future research should focus on expanding the dataset to include more crop species and diseases and improving the model's accuracy and performance to help farmers manage crop diseases and pests more efficiently.

Finally, Deng et al. [14] introduced a state-of-the-art technique utilizing saliency maps, inspired by the human visual system, to swiftly and accurately identify objects of interest. Their study targeted ten categories of insect pests affecting tea plants, each category comprising approximately 40- 70 sample images sourced from various repositories and showcasing diverse conditions. The method integrates several models and methods, including SUN for saliency maps, an extended HMAX model with SIFT and NNSC for feature extraction, an LCP algorithm for texture features, and SVM for recognition. Results indicate an impressive accuracy rate of 85.5%, surpassing existing methods in recognition and processing time. This pioneering approach holds promise for practical deployment in agricultural pest management, contributing to sustainable farming practices and environmental conservation.

Automated pest detection and management in agriculture have advanced with the use of machine learning and deep learning techniques. However, significant gaps remain that need to be addressed for improved efficacy. Notably, while many studies utilize YOLO-based models for pest detection, none have explored the latest YOLOv8 and YOLOv9 versions, which promise enhanced accuracy, speed, and efficiency. Investigating these versions' effectiveness compared to previous iterations is essential. Additionally, existing models largely fail to differentiate between harmful and beneficial pests. This distinction is crucial for targeted pest management and minimizing crop damage. Therefore, we propose to develop a model using YOLOv8, YOLOv9, and VGG16 to effectively classify pests based on their impact on crop health.

## 3. Data Collection

We collected a dataset comprising ten categories of insects frequently encountered in agricultural environments. This dataset was sourced from Kaggle. The complete dataset can be accessed in the designated drive folder [15]. The categories are as follows:

**Harmful Insects:**

- Marmorated Stink Bugs
- Colorado Potato Beetles

- Fall Armyworms
- Western Corn Rootworms
- Thrips

**Harmless Insects:**

- Bees
- Beetles
- Cicadas
- Dragonflies
- Grasshoppers

Each category consists of 100 images, resulting in a total of 1,000 images in the dataset. The dataset is divided into training, validation, and testing sets with proportions of 80%, 10%, and 10%.This allocation results in 800 images for training, 100 images for validation, and 100 images for testing.

## 4. Methodology

### A. Yolo Algorithms

The acronym "YOLO" stands for "You Only Look Once" and is a widely recognized object detection system in the field of computer vision due to its exceptional capabilities [16]. Unlike conventional methods that repeatedly apply detection models across different regions and scales, YOLO integrates the entire detection process into a single neural network that simultaneously predicts multiple bounding boxes and class probabilities. YOLO frames object detection as a single regression problem, directly from image pixels to bounding box coordinates and class probabilities. This unique approach allows YOLO to effectively utilize global image context, enhancing its ability to distinguish foreground objects from background noise and deliver highly accurate predictions swiftly, as YOLO makes less than half the number of background errors compared to Fast R-CNN [17]. This feature is particularly beneficial for real-time applications such as video surveillance and autonomous driving. The system's architecture combines convolutional layers for both detection and classification and is trained on extensive datasets like PASCAL VOC and COCO, enhancing its generalization across various scenes. With its focus on speed and accuracy, YOLO has undergone several refinements to improve its performance and efficiency, making it a vital tool in both academic research and practical applications in object detection.

#### 1. YOLOv9

The YOLOv9 represents the newest iteration of the YOLO, delivering exceptional real-time object detection performance. This version, developed by combining PGI and GELAN, has demonstrated remarkable competitiveness. Its superior design enables the deep model to reduce the parameter count by 49% and the computational workload by 43% compared to YOLOv8, while still achieving a 0.6% AP improvement on the MS COCO dataset [18].

#### 2. YOLOv8

YOLOv8 is another model in the YOLO series for object detection, which precedes YOLOv9. It was unveiled in 2023 and maintains the fundamental architecture of its predecessors while incorporating numerous advancements. These enhancements include a new neural network structure that combines the Feature Pyramid Network (FPN) and the Path Aggregation Network (PAN). Additionally, YOLOv8 introduces an overhauled labeling tool aimed at streamlining the annotation process. This tool offers various advantageous features, such as automatic labeling, shortcut keys for labeling, and customizable hotkeys, all of which contribute to a more efficient method of labeling images for model training [19].

### B. VGG-16

The VGG-16 model is widely celebrated for its outstanding performance in computer vision applications, especially in the areas of image classification and object recognition. This advanced convolutional neural network is predominantly utilized for the purpose of image categorization. It is composed of numerous convolutional layers, each followed by pooling layers, which progressively increase in complexity. This architecture ultimately leads to fully connected layers responsible for the final classification process. Generally, the final layer of the VGG-16 model utilizes a SoftMax activation function, allowing it to effectively categorize images into distinct classes, such as different disease stages. VGG-16 is widely known for its outstanding performance in computer vision tasks, especially in image classification and object recognition. This deep convolutional neural network is mainly used for categorizing images.

### C. Training Methodology

The purpose of this study is to compare previous research findings with new discoveries related to the identification of beneficial and harmful insects on farms using the You Only Look Once (YOLO) and VGG-16 object recognition algorithms. The study evaluates the effectiveness of the Yolo8l, Yolov9-e, and VGG-16 models, which were trained on a dataset of 1000 images distributed across 10 classes, with each class containing 100 images. The models were trained using different hyperparameters, including epochs ranging from 40 to 100 and batch sizes of 8 for yolov8 and yolov9, and 10 for VGG-16.

**Table 1.** The models at different hyperparameters

| Model | Hyperparameters | Value |
|---|---|---|
| **Yolov8l** | Epochs | 40-100 |
| | Batch size | 8 |
| **Yolov9-e** | Epochs | 40-100 |
| | Batch size | 8 |
| **VGG-16** | Epochs | 35-40 |
| | Batch size | 10 |

### D. Training Environment

In order to effectively train our models, we have opted to utilize Google Colab for running our Python code. This decision enables us to leverage advanced computational capabilities, including GPUs, to meet the specific training demands of both the YOLO and VGG-16 models.

## 4. Results and Discussion

In this section, we analyze and compare the performance of three advanced models (YOLOv8, YOLOv9, and VGG-16) based on accuracy, precision, recall, and F1-score across different insect classes.

### A. YOLO Object Detection and Classification

Table 2. YOLOv8 accuracy over epochs

| Model | Epochs | Accuracy |
|---|---|---|
| **YOLOv8** | 40 | 0.81 |
| | 50 | 0.80 |
| | 70 | 0.83 |
| | 100 | 0.81 |

Based on Table 2, we tested the YOLOv8 model over various epochs and observed that it achieved accuracies of 81%, 80%, 83%, and 81% for epochs 40, 50, 70, and 100, respectively. The highest accuracy was found at epoch 70, which was 83%. We will now proceed to calculate the precision, recall, and F1-score for this epoch to further evaluate the model's performance.

We use standardized formulas to measure the performance of our YOLO detection models. These metrics are calculated based on values from the confusion matrix:

- Accuracy : (TP+TN)/(TP+TN+FP+FN)
- Precision: TP/(TP+FP)
- Recall: TP/(TP+FN)
- F1 Score: 2 * (precision * recall) / (precision + recall) [20].

These calculations help us effectively evaluate the performance of our predictive models in distinguishing between different classes.

**Table 3**. Accuracy, precision, recall, and F1-score for each class for Yolov8 at epoch 70

| | Accuracy | Precision | Recall | F1-score |
|---|---|---|---|---|
| **Bees** | 0.975 | 0.884 | 0.84 | 0.862 |
| **Beetles** | 0.986 | 0.905 | 0.95 | 0.927 |
| **Cicada** | 0.969 | 0.816 | 0.848 | 0.832 |
| **Dragonfly** | 0.973 | 0.832 | 0.881 | 0.856 |
| **Grasshopper** | 0.956 | 0.732 | 0.82 | 0.774 |
| **Brown Marmorated Stink Bugs** | 0.983 | 0.977 | 0.842 | 0.904 |
| **Fall Armyworms** | 0.937 | 0.746 | 0.47 | 0.577 |
| **Colorado Potato Beetles** | 0.973 | 0.918 | 0.78 | 0.843 |
| **Thrips** | 0.977 | 0.850 | 0.91 | 0.879 |
| **Western Corn Rootworms** | 0.960 | 0.818 | 0.72 | 0.766 |

Table 3 provides a detailed analysis of the performance of the YOLOv8 model at epoch 70. It includes accuracy, precision, recall, and F1-scores for different insect classes. The model achieves an overall accuracy of 96.89%, calculated by averaging the accuracies for each class as shown in Table 2. Beetles and

Brown Marmorated Stink Bugs stand out with high F1-scores of 0.927 and 0.904, respectively, demonstrating the model's strong identification capabilities. Cicadas and Dragonflies also perform well with F1-scores of 0.832 and 0.856, highlighting the model's effectiveness. However, there are challenges in consistently detecting Fall Armyworms, with a notably low recall of 0.47 and the lowest F1-score of 0.577. Grasshoppers and Thrips show moderate performance with F1-scores of 0.774 and 0.879, indicating areas for improvement. The evaluation also includes Colorado Potato Beetles and Western Corn Rootworms, with F1-scores of 0.843 and 0.766, providing a comprehensive assessment of the model's capabilities at this epoch.

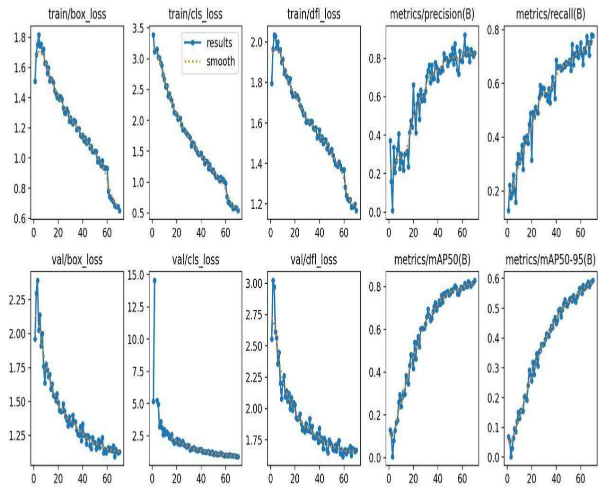


**Figure 1.** Training and Validation Losses of YOLOv8 Model

Table 4. YOLOv9 accuracy over epochs

| Model | Epochs | Accuracy |
|---|---|---|
| **YOLOv9** | 40 | 0.85 |
| | 50 | 0.86 |
| | 70 | 0.83 |
| | 100 | 0.88 |

Figure 1 illustrates the YOLOv8 model's training and validation loss curves and performance metrics. The curves show a consistent decline in various losses over epochs, indicating effective learning and optimization. The precision, recall, and mean Average Precision (mAP) metrics display increasing trends across different IoU thresholds. These improvements directly correlate with enhanced detection capabilities and precision in classification. This visualization encapsulates the model's learning progress, demonstrating its advancing ability to generalize unseen data effectively.

**Figure 2.** Testing sample of YOLOv8 Model

Moving from YOLOv8 to YOLOv9, we observe an improved performance profile. In Table 4, we have documented the performance of the YOLOv9 model across different epochs. The model demonstrated accuracies of 85%, 86%, 83%, and 88% at epochs 40, 50, 70, and 100, respectively. Notably, the epoch 100 showed the highest accuracy, reaching 88%. Following this observation, we will next assess the precision, recall, and F1-score corresponding to this optimal epoch.

**Table 5**. Accuracy, precision, recall, and F1-score for each class for yolov9

| | Accuracy | Precision | Recall | F1-score |
|---|---|---|---|---|
| Bees | 0.991 | 0.95 | 0.95 | 0.95 |
| Beetles | 0.972 | 0.817 | 0.89 | 0.852 |
| Cicada | 0.991 | 0.95 | 0.95 | 0.95 |
| Dragonfly | 0.980 | 0.899 | 0.881 | 0.890 |
| Grasshopper | 0.966 | 0.779 | 0.88 | 0.826 |
| Brown Marmorated Stink Bugs | 0.985 | 1.0 | 0.842 | 0.914 |
| Fall Armyworms | 0.959 | 0.867 | 0.65 | 0.743 |
| Colorado Potato Beetles | 0.972 | 0.856 | 0.83 | 0.843 |
| Thrips | 0.968 | 0.822 | 0.83 | 0.826 |
| Western Corn Rootworms | 0.940 | 0.764 | 0.524 | 0.621 |

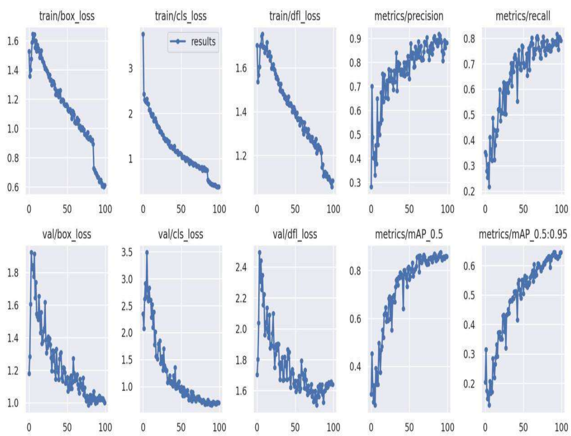


**Figure 3.** Training and Validation Losses of YOLOv9 Model

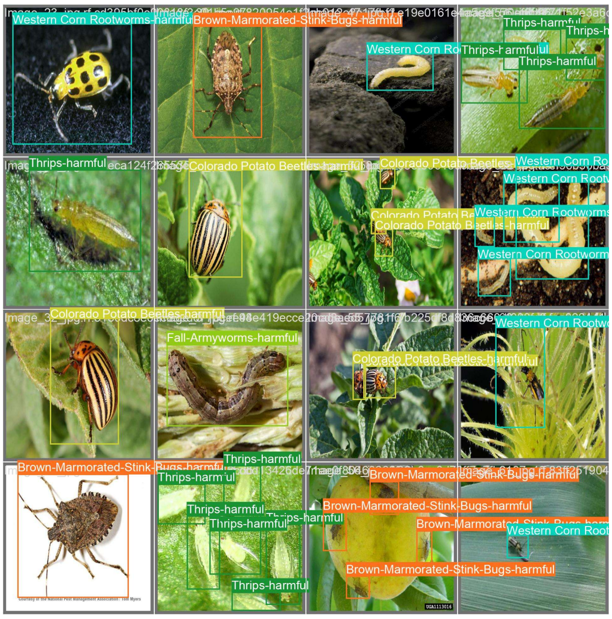


**Figure 4.** Testing sample of YOLOv9 Model

The YOLOv9 model has demonstrated impressive effectiveness in automatically recognizing insects, as shown in Table 4. However, its performance varies across different insect types. Bees and Cicadas have achieved outstanding precision, recall, and F1-scores, all at 0.95, indicating highly accurate detection capabilities. Brown Marmorated Stink Bugs are particularly impressive, achieving a perfect precision of 1.0 and an F1-score of 0.914, reflecting exceptional detection precision. Challenges arise with Western Corn Rootworms and Fall Armyworms, with lower F1-scores of 0.621 and 0.743, respectively, suggesting difficulties in consistent detection. Thrips show moderate performance with an F1-score of 0.826, indicating areas for potential improvement. Overall, the model maintains a strong accuracy of 97.24%, calculated from the average of individual accuracies for each class as detailed in Table 4. While the model shows strong overall accuracy, further refinement in precision and recall is needed for certain challenging categories to optimize pest management strategies in agriculture.

Figure 3 shows the YOLOv9 model's training and validation loss curves and performance metrics, providing insights into the model's learning dynamics over epochs. The graphs illustrate consistent improvement in bounding box predictions, object classification, and attribute estimation. Validation loss curves show some fluctuations but indicate good generalization. Performance metrics confirm increasing accuracy and robustness in object detection tasks.

## B. VGG-16 Neural Network Model

After discussing the impressive performance of the YOLOv9 model, it is important to compare it with the VGG-16 model. While it is a well-established model for classical image processing tasks, it may not be as effective in this particular application.
We utilized the previously mentioned formulas to assess the performance of the VGG-16 classification model in Table 6 [20].

**Table 6**. Accuracy, precision, recall, and F1-score for each class for VGG-16

| | Accuracy | Precision | Recall | F1-score |
|---|---|---|---|---|
| Bees | 0.875 | 0.308 | 0.2 | 0.242 |
| Beetles | 0.839 | 0.25 | 0.35 | 0.292 |
| Cicada | 0.807 | 0.148 | 0.2 | 0.170 |
| Dragonfly | 0.885 | 0.333 | 0.15 | 0.207 |
| Grasshopper | 0.820 | 0.111 | 0.1 | 0.105 |
| Brown Marmorated Stink Bugs | 0.86 | 0.167 | 0.1 | 0.125 |
| Fall Armyworms | 0.863 | 0.294 | 0.25 | 0.270 |
| Colorado Potato Beetles | 0.830 | 0.25 | 0.35 | 0.292 |
| Thrips | 0.871 | 0.286 | 0.2 | 0.235 |
| Western Corn Rootworms | 0.840 | 0.324 | 0.550 | 0.407 |

The performance of the VGG-16 model was evaluated in terms of accuracy, precision, recall, and F1-score, and the results are presented in Table 6. The accuracy of bees was high at 87.5%, but their precision and recall were low, which led to a F1-score of 24.2%. Beetles and Colorado Potato Beetles showed similar effectiveness, each with accuracies around 83% and F1-scores of 29.2%.

Cicadas were the most challenging to recognize with the lowest metrics, including an accuracy of 80.7% and F1-score of 17%. Dragonflies achieved an accuracy of 88.5%, but their recall was disappointing at 15%, resulting in an F1 score of 20.7%. Grasshoppers and Brown Marmorated Stink Bugs were poorly recognized, with minimal F1-scores of 10.5% and 12.5%, respectively. Fall Armyworms and Thrips showed moderate performance with accuracies around 86% and required improvements in precision and recall. Western Corn Rootworms, on the other hand, excelled with the highest recall of 55% and F1-score of 40.7%, indicating effective identification.

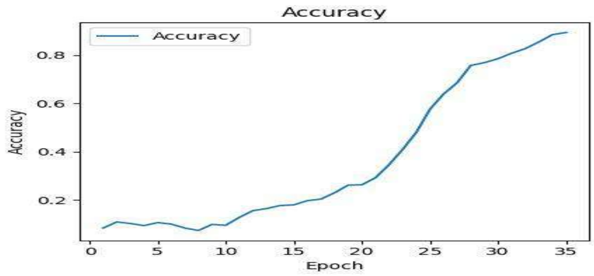


**Figure 5.** Training Accuracy of VGG-16 Model

Moreover, Figure 5 shows the training progression of the model and aligns with these findings, exhibiting an initial low accuracy that significantly improves after the 20th epoch, indicating the model's enhanced ability to generalize and recognize features more effectively with continued training. This figure demonstrates how the model's learning curve correlates with the observed metrics, where certain insects like Western Corn Rootworms show distinct improvement in later training phases.

## C. Overall Comparison

**Table 7.** YOLOv8, YOLOv9, and VGG-16 accuracy

| Model | Accuracy |
|---|---|
| **YOLOv8** | 0.969 |
| **YOLOv9** | 0.972 |
| **VGG-16** | 0.849 |

Based on the evaluation of three models, it is clear that the YOLOv9 model outperforms the other two, as shown in Table 7. The YOLOv9 model has consistently high metrics across various insect classes, which demonstrates its superiority. It has particularly impressive achievements in terms of precision, recall, and F1 scores for classes such as Bees and Cicadas, where it reaches metrics close to perfection. The model has also shown excellent precision with a perfect score for Brown Marmorated Stink Bugs, along with a strong F1 score. Moreover, the YOLOv9 model achieves an accuracy of 97.2%, which is remarkable (Table 7). Although the YOLOv8 and VGG-16 models also perform well in certain classes, the YOLOv9 model maintains higher consistency and balance across essential performance indicators, with YOLOv8 achieving 96.9% and VGG-16 lagging at 84.9% accuracy. Hence, YOLOv9 is the most reliable model for practical applications in agricultural pest management, accurately detecting various insect types and exhibiting superior generalization capabilities. Leveraging YOLOv9's robust framework could significantly enhance pest detection and management strategies, contributing to more effective and sustainable agricultural practices in the future.

## 5. Conclusion

In conclusion, our study highlights the efficacy of advanced object detection models in distinguishing between harmful and harmless insects within agricultural settings, thereby potentially reducing economic losses due to pest damage. Our comparative analysis of YOLO versions 8 and 9, along with VGG-16, revealed that YOLOv9 outperforms the other models with the highest accuracy rate of 0.972. This superior performance underscores the advantages of utilizing YOLOv9 for real-time, accurate pest detection and classification. While VGG-16 showed lower accuracy, it still holds value for certain applications that may not require the highest precision. Future work should focus on further refining these models, expanding the dataset to include a broader range of insect classes, and integrating these models into a user-friendly tool for farmers and agricultural professionals. By continuing to advance and optimize these detection technologies, we can enhance pest management strategies and safeguard crop yields more effectively.

## References

[1] M. C. F. Lima, M. E. D. De Almeida Leandro, C. Valero, L. C. P. Coronel, and C. O. G. Bazzo, “Automatic Detection and Monitoring of Insect Pests—A Review,” Agriculture, vol. 10, no. 5, p. 161, May 2020, doi: 10.3390/agriculture10050161.

[2] T. Saidani, R. Ghodhbani, A. Alhomoud, A. Alshammari, H. Zayani, and M. B. Ammar, “Hardware Acceleration for Object Detection using YOLOv5 Deep Learning Algorithm on Xilinx Zynq FPGA Platform,” Engineering, Technology and Applied Science Research/Engineering, Technology and Applied Science Research, vol. 14, no. 1, pp. 13066–13071, Feb. 2024, doi: 10.48084/etasr.6761.

[3] D. Hindarto, N. Afarini, and E. T. E. H, “Comparison efficacy of VGG16 and VGG19 insect classification models,” Jurnal Informatika Dan Komputer/JIKO (Jurnal Informatika Dan Komputer), vol. 6, no. 3, pp. 189–195, Dec. 2023, doi: 10.33387/jiko.v6i3.7008.

[4] D. Ruaika and S. 'Uyun, "Optimisation of Residual Network Using Data Augmentation and Ensemble Deep Learning for Butterfly Image Classification," IJID (International Journal on Informatics for Development), vol. 12, no. 2, pp. 350-361, Dec. 2023, doi: 10.14421/ijid.2023.4038.

[5] Kumar, N., Nagarathna, & Flammini, F. (2023) Yolo-based light-weight deep learning models for insect detection system with field adaption. MDPI. Available at: https://www.mdpi.com/2077-0472/13/3/741

[6] Betti Sorbelli, Francesco & Palazzetti, Lorenzo & Pinotti, Cristina. (2023). YOLO-based Detection of Halyomorpha halys in Orchards Using RGB Cameras and Drones. 10.1016/j.compag.2023.108228.

[7] T. Stark et al., "YOLO object detection models can locate and classify broad groups of flower-visiting arthropods in images," Sci. Rep., vol. 13, article no. 16364, 2023. [Online]. Available: https://doi.org/10.1038/s41598-023-43482-3

[8] Anwar, Z. and Masood, S. (2023) Exploring deep ensemble model for insect and Pest detection from images, Procedia Computer Science. Available at: https://www.sciencedirect.com/science/article/pii/S187705092300208

[9] Wen, C., Chen, H., Ma, Z., Zhang, T., Yang, C., Su, H., & Chen, H. (2022). Pest-YOLO: A model for large-scale multi-class dense and tiny pest detection and counting. Front. Plant Sci., 13, 973985. doi: 10.3389/fpls.2022.973985.

[10] Kasinathan, T., Singaraju, D., & Reddy, U. S. (2021). Insect classification and detection in field crops using modern machine learning techniques. Information Processing in Agriculture, 8(3), 446–457. doi: 10.1016/j.inpa.2020.09.006.

[11] Marković, D., Vujičić, D., Tanasković, S., Đorđević, B., Ranđić, S., & Stamenković, Z. (2021). Prediction of pest insect appearance using sensors and machine learning. Sensors (Basel), 21(14), 4846. doi: 10.3390/s21144846.

[12] Gupta, Y., & Homchan, S. (2021). Short communication: Insect detection using a machine learning model. Nusantara Bioscience, 13(1). doi: 10.13057/nusbiosci/n130110.

[13] Ai, Y., Sun, C., Tie, J., & Cai, X. (2020). Research on recognition model of crop diseases and insect pests based on deep learning in harsh environments. IEEE Access, 8, 171686–171693. doi: 10.1109/access.2020.3025325.

[14] Deng, L., Wang, Y., Han, Z., & Yu, R. (2018). Research on insect pest image detection and recognition based on bio-

inspired methods. Biosystems Engineering, 169, 139–148. doi: 10.1016/j.biosystemseng.2018.02.008

[15] Insects (2024) Google Drive. Available at: https://drive.google.com/drive/folders/1yIKxzwgKhg33F9SnRqKV9TepRxiILl4A?usp=sharing

[16] Jiang, P., Ergu, D., Liu, F., Cai, Y., & Ma, B. (2022). A review of Yolo algorithm developments. Procedia Computer Science, 199, 1066–1073. https://doi.org/10.1016/j.procs.2022.01.135

[17] J. Redmon et al., "You Only Look Once: Unified, Real-Time Object Detection," in 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2016, pp. 779-788

[18] C. Wang, I. Yeh, and H. Liao, "YOLOv9: Learning What You Want to Learn Using Programmable Gradient Information," ArXiv, abs/2402.13616, 2024.

[19] D. Reis, J. Kupec, J. Hong, and A. Daoudi, "Real-Time Flying Object Detection with YOLOv8," ArXiv, abs/2305.09972, 2023.

[20] H. N. B, "Confusion matrix, accuracy, precision, recall, F1 score," Medium, Dec. 12, 2021. [Online]. Available: https://medium.com/analytics-vidhya/confusion-matrix-accuracy-precision-recall-f1-score-ade299cf63cd