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Research Article

A Unified Deep Learning Framework for Accurate Pest Detection and Classification in Agriculture

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ABSTRACT

Introduction: Agriculture is an important role in sustaining human life and ensuring high quality food production is essential for economic growth. Among the main difficulties farmers encounter the rapid spread of insect and pest infestations which can significantly impact crop yields.

Objectives: While, existing approaches have explored pest detection and classification, often suffer from inaccuracies and inefficiencies. To address these issues, this paper propose a unified Approach for PEST detection and classification model called SAMYNET (Segment Anything Model + YOLO8 + EfficientNet system).

Methods: SAMYNET an advanced automated system in that combines three cutting-edge DL models: Yolov8 for object detection, Segment Anything Model (SAM) for image segmentation, and EfficientNet for fine-grained classification. The system runs in a pipeline with several stages..

Results: To begin with, YOLOv8 is used to identify probable pests in the crop photos and create bounding boxes around them. SAM then processes these identified areas of interest (ROIs) to generate accurate segmentation masks for every pest, defining their precise borders.

Conclusions: Finally, EfficientNet classifies each segmented pest into specific categories providing detailed identification. Experimental results demonstrate that SAMYNET outperforms traditional methods in pest detection, segmentation and classification achieving high accuracy of 95% and precision 89%. This automated system offers farmers and agricultural experts a scalable, efficient tool for timely pest management which ultimately crop yields and promoting sustainable agricultural practices.

Keywords: Pest detection, agricultural production, Insect detection, YOLOv8, SAM and EfficientNet CNN.

INTRODUCTION

In modern agriculture, protection and management are crucial for maintaining crop health and productivity which form the backbone of the global food supply. Climate change, evolving pest behaviors, and inadequate agricultural practices exacerbate the challenges faced in pest management. Pests are estimated to be responsible for up to 40% of global crop yield losses annually, significantly impacting food security and economic stability. For instance, rice yield losses caused by brown planthoppers in Southeast Asia and maize losses due to fall armyworms in Africa demonstrate the devastating effects of unchecked pest infestations. These issues are further compounded by the growing global population and the increasing impact of climate change on agricultural ecosystems.

Conventional manual techniques for identifying pests, like visual inspection using magnifying glasses, are time-consuming, labour intensive, and prone to errors. While early computer vision techniques using contour analysis, edge detection, and background removal provided some advancements, they fall short in addressing the diverse environmental conditions and complex pest variations found in modern agriculture.

This work proposes a unique framework, SAMYNET (Segment Anything Model + YOLO8 + EfficientNet system), which combines advanced DL approaches to overcome these issues. for pest detection and classification. The framework utilizes YOLOv8 for object detection, SAM (Segment Anything Model) for multi-dimensional segmentation, and EfficientNet CNN for precise pest classification. By employing these advanced models, SAMYNET ensures accurate pest identification and categorization, enabling targeted pesticide application and reducing crop losses effectively.

This paper makes the following key contributions:

- Proposing a unified DL based framework, SAMYNET, for pest detection and classification.
- Integrating YOLOv8, SAM, and EfficientNet CNN to achieve high detection accuracy and efficiency under diverse conditions.
- Demonstrating the applicability of SAMYNET through comprehensive experiments, showcasing improved detection accuracy and reduced processing time.
- The rest of the manuscript is structured as follows: In Section 2, relevant literature is reviewed; in Section 3, the proposed method is explained; in Section 4, experimental data and analysis are presented; and in Section 5 provides conclusion with future scope are suggested.

LITERATURE REVIEW

Identifying and controlling pests is essential to preserving crop health and yield in contemporary agriculture, especially for staple crops like rice and maize, which form the backbone of the global food supply. Climate change, evolving pest behaviours, and inadequate agricultural practices exacerbate the challenges faced in pest management. The subject of pest identification and forecasting has made considerable progress with advancements in DL. However, several critical challenges remain unresolved, particularly in terms of generalization, efficiency, and scalability. Table 1 summarizing the strengths and weaknesses in the pest management in the agriculture.

Table 1: Summary review of pest management in the agriculture

no	**Author name**	**Strengths**	**Weakness**
1	Bhat et.al (2024)[1]	Promotes long-term sustainable agriculture with a focus on safe, quality food production.	Requires careful planning and monitoring, which may be resource-intensive for small farmers.
2	Venkatasaichandrakanth (2024) [2]	Highlights the importance of pest detection for improving crop quality and agricultural growth.	Limited discussion on specific economic data or examples of how pest detection directly boosts agricultural economies.
3	Bouri, M et.al (2023) [3]	Supports sustainable agricultural development by addressing climate-related phytosanitary issues.	Decision-making difficulties due to unpredictable weather and complex climate models.
4	Liu et.al (2022)[4]	Focus on forecasting agricultural processes; highlights the importance of pest detection and classification.	Limited discussion on specific detection methodologies and their application in diverse environmental conditions.
5	Qiulin WU et.al (2022) [5]	Combines pest management with sustainable agriculture goals to combat food security challenges.	Heavy reliance on chemical pesticides, making China the largest pesticide consumer globally.

Thenmozhi et al. [6] explored the improvement of classification accuracy and computation time for recognizing insects in field crops. Their approach demonstrated the potential to identify pests in early stages, thereby enhancing crop yield and quality. However, the study focused narrowly on specific crop types and lacked adaptability to diverse agricultural conditions.

Zhe et al. [7] used an efficient channel attention method and a transformer encoder to increase feature extraction and capture global contextual information. While this approach enhanced the CNN architecture's capabilities, the increased complexity posed challenges for real-time deployment in agricultural scenarios.

Everton et al. [8] demonstrated that YOLOv3, trained with optimized batch sizes, achieved higher detection rates in soybean fields. Although effective, the model's application was limited to specific crops, and it struggled to generalize across varying pest types and environmental conditions.

Yunong et al. [9] created the multi-scale Dense YOLO for detecting small target pests on sticky bug's boards. Their improvements in accuracy showcased the potential of multi-scale feature extraction. However, the method was restricted to stationary boards, limiting its application in dynamic agricultural environments.

Research Gaps and SAMYNET's Contributions

While existing studies have advanced pest detection techniques, they share common limitations, such as reliance on constrained datasets, lack of generalization, and limited real-world deployment capabilities. Most models fail to handle diverse agricultural conditions, novel pest species, and varying environmental factors effectively.

To address these challenges, SAMYNET integrates state-of-the-art models:

- EfficientNet: Enhances classification accuracy with efficient feature extraction.
- YOLOv8: Provides quick and accurate object detection in real-time.
- Segment Anything Model (SAM): Ensures robust segmentation across varying image dimensions.

This integrated framework overcomes the limitations of existing approaches by improving detection precision, adaptability to diverse conditions, and scalability.

PROPOSED ALGORITHM: SAMYNET

Pest detection and classification in agricultural refers to the process of identifying and categorizing harmful pests in crops to enable timely and effective pest management, ensuring improved crop health and yield. Previous research on pest detection and classification has faced various shortcomings, including low detection accuracy, inefficient pest segmentation, and a lack of resilience in discriminating between identical pest species. Many traditional methods rely on single-stage detection models or manual processes, which are time-consuming and error-prone, especially in complex agricultural situations with shifting lighting, backdrops, and overlapping items. To meet these issues, the proposed SAMYNET system combines three advanced deep learning (DL) models into a single pipeline. The SAMYNET model has four modules. This is explained in the Figure 1. Initially, YOLOv8 detects possible pests in crop photos and creates bounding boxes around areas of interest. These regions are subsequently analyzed by SAM, which generates very accurate segmentation masks that indicate the precise borders of each pest, overcoming the coarse and inconsistent segmentation of previous approaches. Finally, EfficientNet categorizes the segmented pests, allowing for more precise identification at a finer level. SAMYNET addresses the inadequacies of earlier systems by merging object detection, segmentation, and classification into a unified framework, resulting in a scalable, accurate, and effective pest management solution in agriculture.

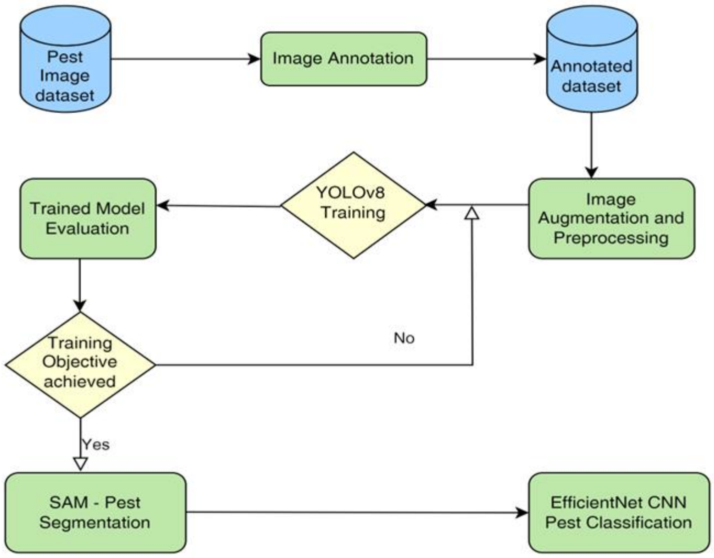

Figure 1. Schematic flow process of the SAMYNET

Pre-processing

In the pre-processing of SAMYNET includes the following steps:

Step 1: Data Collection

The pest images are being taken manually from the internet. The size of the database can be numerous. On this approach, we use seven unique types of pests particularly Grasshopper, purple Bollworm, Rice Hispa, Fall Armyworm, Brown Planthopper, Whiteflies, and Aphids. These pests are present on leaves and vegetation. The database consists of pest photos which are captured from diverse angles. For non-real-time purposes, the database is prepared by manually gathering the pix where the pests are present. In actual-time conditions, the photo is captured by using the photograph acquisition toolbox in MATLAB. The input image which consists of pests is being pre-processed before the segmentation manner.

For the purpose of training and validating the insect pest detection system, images were collected from various online sources. The focus of this research was to identify and classify 23 distinct categories of insect pests. During data collection, several databases and search engines, including Kaggle, Google, Baidu, iStock, Dreamstime, Flickr, and Bing, were utilized. A total of 7,046 images were gathered and subsequently categorized into 23 distinct classes, as outlined in Table 1. To ensure uniformity, all images were resized to 640 × 640 pixels, maintaining consistent width and height dimensions.

Step 2: Data Augmentation

Data augmentation is a critical step in preprocessing that artificially expands the dataset by generating modified versions of the collected images. This allows to enhance the robustness and generalization of the SAMYNET model by exposing it to variations that simulate real-world scenarios.

The SAMYNET uses three techniques in the data augmentation like Rotation, Scaling and flipping. To mimics the pests at various orientations and improvising the detection of pests by applying the rotation angles of 90°, 180°, and 270°. To simulate a mirrored view of pests or inverted crop images, enhancing model adaptability by applying the vertical and horizontal flips. To Helps the SAMYNET to recognize pests at varying sizes and distances by applying the scaling operation. Resize the pest regions within the image, either enlarging or shrinking them while maintaining aspect ratio. Resizing the image from the database to the size required by the networks used in the methodology is part of the pre-processing of the image. Two networks are being used, and the input image is being resized without affecting the original image's aspect ratio. An image's height to width ratio is known as its aspect ratio. The only pre-processing operation carried out is the resizing operation. YOLOv8 object detection and SAM (Segment Anything Model) segmentation remove noise and uneven sunlight illumination.

Step 3: Data Annotation

Image Annotation is a crucial initial step in preprocessing images before training DL models. The data's feature extraction from an image is determined, based on the inputs of chosen functions. During training, the machine learns functions from the classified image. For this reason, the accuracy of the characteristic labels notably influences the model's schooling accuracy. Because of the similarity of many pest species, DL models want to study functions unique to different pests. The annotation system entails marking the species and places of insect pests on the tagged image, supplying coordinates and bounding containers for pests of varying kinds and sizes.

The tool LabelImg is a graphical image labeling tool that is open-source [19].

Module 2: How YOLOV8

To improve the accuracy and precision in the detection of pest in the crop YOLOV8 plays a vital role. YOLOV8 is used for bounding box regression and object classification. It enhancing the better anchor-free based detection and adaptive label assignment to better localization of object in the agricultural based images for detection of pest.

Module 3: SAM (Segment Anything Model):

Function: When provided a prompt, SAM may segment any item in an image. It can produce excellent segmentation masks for objects using a variety of prompt formats, including text, boxes, and points.

Use Case inside the Framework: Following object detection and bounding box generation by YOLO, SAM may be used to fine-tune these detections by producing accurate segmentation masks for every object that is found. This enables pixel-perfect comprehension of object boundaries and increases the granularity of object recognition.

SAM may segment any item in an image. It can produce excellent segmentation masks for objects using a variety of prompt formats, including text, points, and boxes. It is an efficient tool for identifying boundary of the object. SAM is leveraged to refine YOLOv8's bounding box outputs. For the input, YOLOv8 is used to detect the Region of Interest (ROI) are passed as prompts to SAM produces the highly precise segmentation masks for the detected pests, ensuring fine-grained boundary identification. To improvising the effective detection of boundary parametric selection is required. The parameters are type of prompt, mask quality threshold value. The prompt type is generated by YOLOv8 and it is used for segmentation. Similarly the high threshold value is used to set the high confidence masks and which were used to retained the mask quality. After the segmentation process over and the outputs of SAM is passed into EfficientNet for classification. This two-step refinement ensures high granularity in pest identification.

Module 4: EfficientNet

Function: Compared to older models, the EfficientNet family of convolutional neural networks provides advanced precision while consuming a number of magnitude less parameters and FLOPS (Floating Point Operations Per Second). It employs a compound scaling technique that scales depth, breadth, and resolution all in the same way. The architecture diagram of EfficientNet-B0 is given in Figure 2.

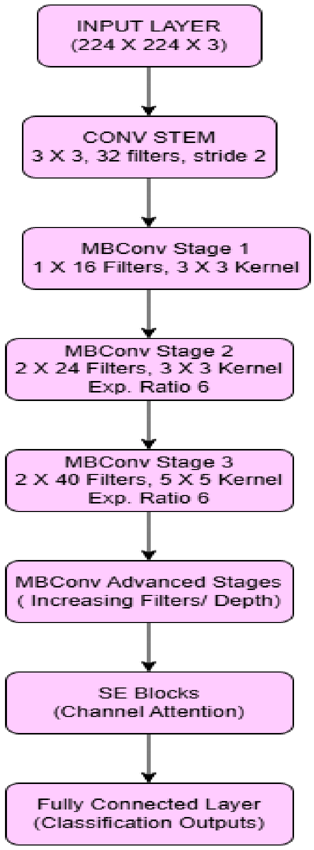

Figure 2 Structure of EfficientNet-B0

The architecture of EfficientNet-B0, which was used in this study, consists of:

1. Input Layer: Accepts images resized to $224 \times 224 \times 3$ (for EfficientNet-B0).

It accepts input images that are downsized to a fixed dimension of 224×224 pixels with three color channels (RGB).

2. Convolutional Stem

A single convolutional layer's kernel size is 3×3 with 32 filters for the extraction of low-level features and stride 2 for downsampling the input image.

3. MBConv Stage 1

One layer of Mobile Inverted Bottleneck Convolutions (MBConv). The kernel size is 3×3 with 16 filters and no expansion ratio (1x expansion).

4. MBConv Stage 2

The two layers of MBConv with kernel size is 3×3 with 24 filters and Expansion ratio of 6, which increases the number of feature maps before applying convolution, enhancing feature extraction.

5. MBConv Stage 3

Two layers of MBConv with a 5×5 kernel size with 40 filters and Expansion ratio of 6 for deeper feature representation.

6. MBConv Advanced Stages

These stages progressively increase the number of filters and the depth of the network, allowing for the extraction of highly detailed and specific features. The architecture scales parameters like depth, breadth, and resolution using a compound scaling approach.

7. SE Blocks

Squeeze and Excitation (SE) blocks are incorporated within the MBConv layers. Focus on channel-wise attention by recalibrating feature importance.

8. Fully Connected Layer

The final dense layer produces classification outputs. For this framework, the layer is adjusted to classify 23 insect pest categories instead of the default 1,000 outputs.

Module 4: SAMYNET

Real-time object detection is provided by YOLO (You Look Only Once). Currently available are various object detection methods, such as You Look Only Once (YOLO) v2, v3, and v9 and Regional Convolution Neural Network. The YOLOv8 Object Detector is what we use to detect this pest. Yolov8 object detector adds detection at various scales to help detect small objects, improving upon Yolo version 8 object detector. The segmentation process uses SAM (Segment Anything Model), and the YOLO v8 is adequate for pest detection on the crops. Ground truth preparation is the first step in the YOLOv8 pest detection process. The pest's bounding box in an image is made using the image Labeler. Each and every image in the database requires a bounding box to be created. Once the bounding boxes are created, use SAM (Segment Anything Model) to turn them into segmented masks before loading the network's necessary layers. The next stage is to configure the training parameters, which include the classifier to be used, the minimum batch size, the starting learning rate, the maximum size of the epoch, and the checklist path. For specific iterations, the network is trained.

RESULTS AND DISCUSSION

This part provides the results of the proposed SAMYNET system for recognizing pests and assessment in agricultural settings. The results are analyzed to evaluate the framework's performance in terms of accuracy, efficiency, and robustness under varying conditions. The discussion highlights the practical implications of the findings and compares them with existing approaches. Key aspects, including the effectiveness of the segmentation (via SAM), classification (via EfficientNet), and integration of object detection (via YOLO), are assessed to demonstrate the framework's contribution to precise pest management.

Dataset Collection

To develop a robust insect pest detection system, images were sourced from a variety of online platforms. The primary objective was to identify and detect 23 distinct categories of insect pests. The image collection process involved retrieving images from multiple databases and search engines including Kaggle, Baidu, istock, Dream, Flickr and Bing. A total of 7,046 images were gathered and systematically classified into 23 distinct categories as presented in Table 2 highlighting the number of images and their corresponding pest categories and samples of image from dataset is illustrated in Figure 3. To ensure uniformity in image dimensions all collected images were resized to 640 × 640 pixels maintaining a consistent width and height. The Figure 4 depicts the datas utilizing for training and validation. The implementation of proposed framework was carried out using MATLAB enabling an efficient and controlled development environment. This holistic approach to pest detection aims to support precision agriculture by facilitating accurate and timely identification of insect pests.

Table 2. Information about the gathered dataset of IP-23 photos.

ID	Name	Number of Samples
1	Aphid	325
2	Bees	320
3	Beetle	322
4	Caterpillar	325
5	Centipede	325
6	Cockroach	325
7	Damselfly	329
8	Grasshopper	325
9	Grub	325

10	Jassid	325
11	Katydid	325
12	Ladybugs	292
13	Locust	325
14	Mantis	325
15	Ant	291
16	Mealybugs	258
17	Root-borer	265
18	Snail	301
19	Spittlebugs	332
20	Termite	210
21	Thrips	293
22	Weevil	305
23	Whitefly	278

Figure 3 Input images in the database

Figure 4. The object detection model was trained and validated using images from the IP-23 dataset.

Performance Metrics

When evaluating a pruning algorithm like SAMYNET, there are several variables to take into account, including accuracy, size, and calculation time. In order to assess how well the model accomplishes its duty, accuracy is required. Model size is the amount of storage space a model requires in bytes. This is easier to quantify than inference time, as it is independent of the platform that the model is run on. Efficiency and model performance are traded off with pruning. If extensively prune is done, the network becomes smaller and more effective, but less accurate. The following performance metrics were used to evaluate the models.

$$Precision = \frac{TP}{TP+FP} \tag{1}$$

$$Recall = \frac{TP}{TP+FN} \tag{2}$$

$$Accuracy = \frac{TP+TP}{TP+FN+TN+FP} \tag{3}$$

$$F1 = 2 \times \frac{Precision \times Recall}{Precision+Recall} \tag{4}$$

Results Analysis

Figure 5 shows the location and kind of insect recognized and recorded in a text document. This file contains a list of every object, including its class, height, and width for the bounding box. A range of 0 to 1 is used to normalize the rectangle's coordinates. The training set also experienced data augmentation processing. By increasing the number of samples in the IP-23 dataset, it was possible to better extract features of insect pests that fall into various labelled categories and avoid overfitting of the trained model.

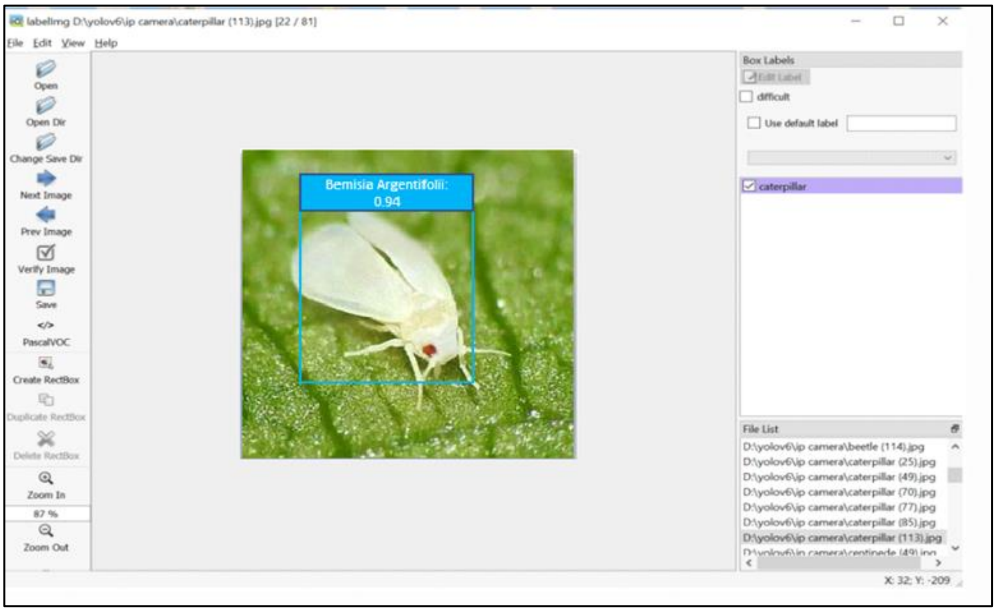

Figure 5. Image Annotation tool and Labelling

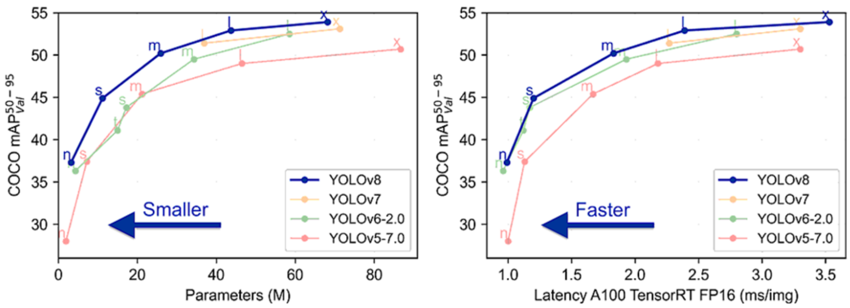

Figure 6. A comparison of other YOLO models with YOLOv8

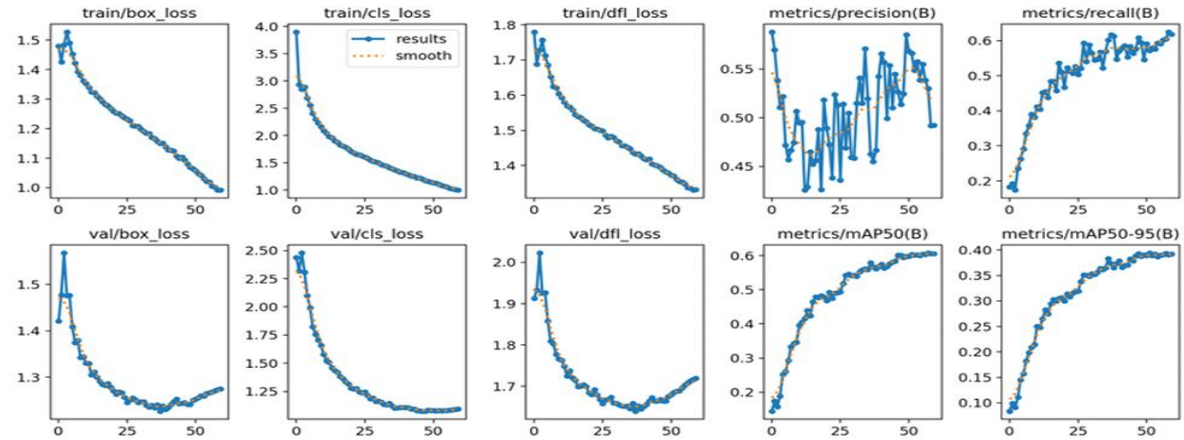

Figure 7. Training of YOLOv8 Network

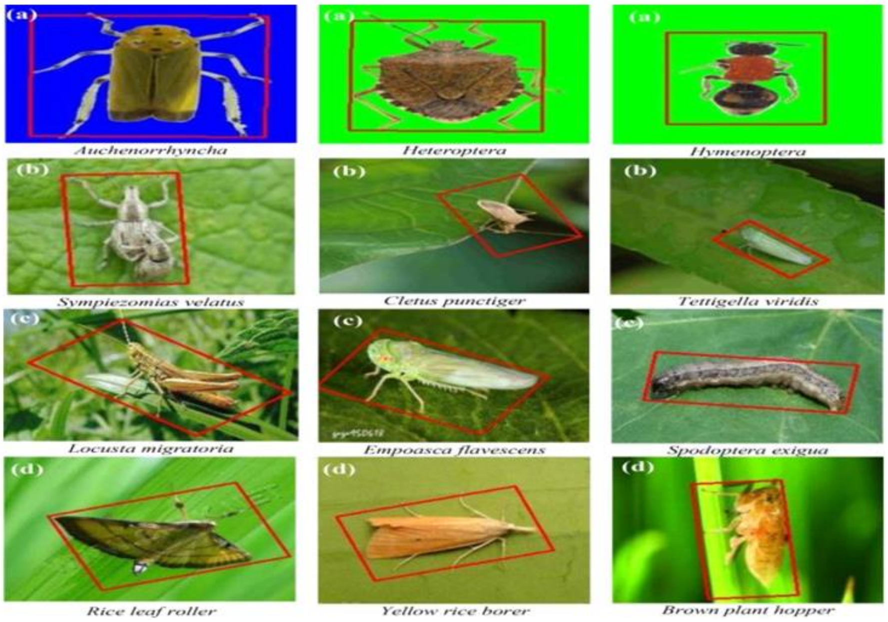

Figure 8. Region of Interest (ROI) of Pest

Pest detection

YOLOv8's output allows for the identification of pests in a picture. The pests on the crop that have been found are not easily eliminated; instead, they need to be segmented using the Segment Anything Model (SAM) and then classified to identify the exact type of bug that is there. The EfficientNet CNN receives the ROI of the picture and classifies any pests that are present. The network in this method recognizes the seven different types of pests that are present in the input image.

EfficientNet CNN

To classify images, EfficientNet is employed. The pest is identified using EfficientNet, and the pest is detected using Yolov8 + SAM. An input image's pests are labeled using EfficientNet. We must train the EfficientNet network in the same way as the YOLOv8 network because it is a CNN. A pre-trained neural network must be loaded in the first step. The next stage is to modify the pre-trained network after reviewing the layered architecture. Together with the change in the maxEpochs and minibatch size, this also modifies the fully connected layer and classification layers. According to the necessary network, the training options are configured. The last phase in the EfficientNet CNN process is training. The network is going to be trained, and we can see a graphical depiction of the process.

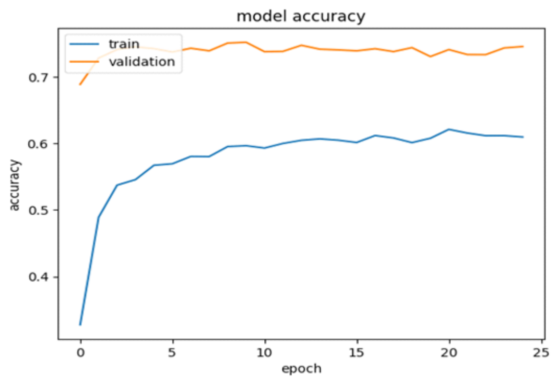

Figure 9. Training of EfficientNet CNN

Pest Classification

Following training, identifying the pests in the image is the last step. In the input image, the pest's name is provided by the pest classification. Pests are being identified and categorized as either one or several.

Pests are identified by being labelled and can be detected using a bounding box around them. This is the result of the pest detection and classification process which is represented graphically using the graphical user interface. The detection button on the GUI is pressed after browsing the image from the database, which causes the output of the pest detection and classification to be shown. Images of a single pest or several pests can be used to observe identification and categorization of pests. The results for both a single and several pests are displayed in the following figures.

Figure 7. Output for Fall Armyworm detection and identification in the image

Figure 8. Output for multiple Whiteflies detection and identification in the image

The Confusion matrix is a matrix in Figure 9 that allows visualizing the efficiency of the classification ML models and its performance values are represented in Table 3

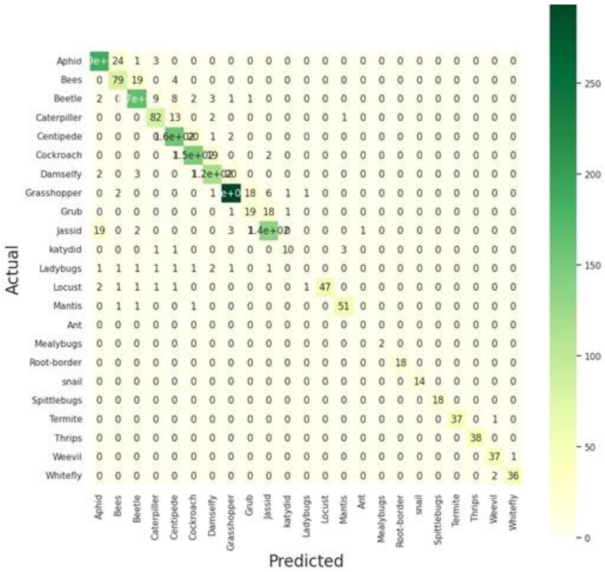

Figure 9: Confusion Matrix of Customized CNN

Table 3: Performance values achieved for 23 different pests

	Precision	recall	f1-score	Support
Aphid	0.88	0.87	0.87	214
Bees	0.73	0.72	0.75	102
Beetle	0.86	0.86	0.86	192
Caterpillar	0.85	0.84	0.84	98
Centipede	0.84	0.87	0.86	179
Cockroach	0.85	0.87	0.86	169
Damselfly	0.81	0.82	0.81	143
Grasshopper	0.91	0.91	0.91	325
Grub	0.49	0.49	0.49	39
Jassid	0.83	0.84	0.84	161
Katydid	0.83	0.67	0.74	15
Ladybugs	0.00	0.00	0.00	10
Locust	1.00	0.87	0.93	54
Mantis	0.93	0.94	0.94	54
Ant	0.00	0.00	0.00	0
Mealybugs	1.00	1.00	1.00	2
Root-borer	1.00	1.00	1.00	18
Snail	1.00	1.00	1.00	14
Spittlebugs	1.00	1.00	1.00	18
Termite	1.00	0.97	0.99	38
Thrips	1.00	1.00	1.00	38
Weevil	0.93	0.97	0.95	38
Whitefly	0.97	0.95	0.96	38
Accuracy			0.86	1959
macro avg	0.81	0.81	0.81	1959
weighted avg	0.86	0.86	0.86	1959

The performance comparison of YOLOv8 which paired with EfficientNet, and SAMYNET reveals significant gains made by the proposed model which is depicted in Table 4. YOLOv8 alone achieves an accuracy of 89% and a precision of 0.77, demonstrating that it can detect pests but has some limitations in classification precision. When paired with EfficientNet, accuracy climbs to 90.54% and precision to 0.82, demonstrating the value of including a fine-grained classification model to boost detection performance. However, the most noteworthy increase is SAMYNET, which achieves an amazing 95% accuracy and 0.89 precision. This indicates that combining YOLOv8 for detection, SAM for segmentation, and EfficientNet for classification produces a more accurate and dependable pest detection system. SAMYNET surpasses both previous models by delivering better pest detection, segmentation, and classification, making it a more effective alternative for automated pest management in agriculture.

Table 4: Comparitive performances

Algorithm	Accuracy	Precision
YOLO V8	89%	0.77
YOLO V8 + EfficientNET	90.54%	0.82
SAMYNET	95%	0.89

This research on SAMYNET represents a significant improvement in the field of automated insect identification and classification in agriculture. By merging three cutting-edge DL models—YOLOv8 for object recognition, Segment Anything Model (SAM) for segmentation, and EfficientNet for classification—the proposed system tackles fundamental shortcomings in existing methods. The results show that SAMYNET surpasses previous approaches by reaching 95% accuracy and 0.89 precision. This enhancement is owing to the successful incorporation of detection, segmentation, and classification tasks, all of which contribute to improved overall performance. YOLOv8 effectively detects and locates pests in photos, while SAM ensures exact segmentation, allowing for more accurate border demarcation. Finally, EfficientNet's fine-grained classification aids in discriminating between pest subcategories, hence enhancing the model's capacity to detect individual pests. These advantages make SAMYNET a more accurate pest identification tool, as well as a more scalable and robust system that can be used in a variety of agricultural situations. This study emphasizes DL's potential to transform pest control by offering farmers a reliable, dependable, and effective tool for improving agricultural yields and mitigating the impact of pest infestations. More research might focus on developing the model to detect a broader range of pests, dealing with a variety of environmental circumstances, and including real-time deployment mechanisms for practical field application.

CONCLUSION

The proposed SAMYNET model represents a substantial development in the field of pest identification and categorization in agriculture. By combining three cutting-edge DL models—YOLOv8 for object recognition, Segment Anything Model (SAM) for image segmentation, and EfficientNet for classification—SAMYNET offers a unified and highly efficient solution. The model's ability to achieve 95% accuracy and 0.89 precision proves its superiority over traditional approaches, overcoming critical limits in detection accuracy and processing time. SAMYNET's multi-stage pipeline enables accurate pest identification, segmentation, and classification, making it a valuable tool for automated pest management. However, obstacles including the need for rapid processing and high-quality annotated data in dynamic situations persist, SAMYNET holds significant promise for increasing crop output, improving pest management procedures, and boosting agricultural sustainability. To improve the model's resilience and adaptability, subsequent research could concentrate on making it more feasible for use in a range of agricultural contexts.

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