Automated Diagnosis of the Severity of TMB Infestation in Cashew Plants Using YOLOv5

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***Abstract*—The cashew (*Anacardium occidentale* L.) is one of the most important commercial crops grown globally. However, the Tea Mosquito Bug (TMB), the major pest of cashew plants may cause significant damage during the flushing, flowering, and fruiting period. Early detection of TMB insect pests in cashew plants is crucial for effective management and control of the infestation. In this research, a computer vision-based approach using the YOLOv5 algorithm is proposed to automatically detect and classify the severity of TMB infestation in cashew plants. The labeled image dataset of cashew plant images encompasses the images of healthy cashew plants and TMB-infested cashew plants of different levels of severity (mild, moderate, severe, and extreme). This dataset is used to train the model to detect and classify the lesions, using Python, OpenCV, and Torch. Experimental results showed that the proposed approach achieved high performance in detecting and classifying the infestations. The performance of the trained model is assessed using a range of metrics, including precision, recall, and F1-Score. Specifically, the precision is measured as 92.6%, the recall as 90.9%, and the F1-Score as 92.4% for all classes. This model can be used as a tool for early detection and diagnosis of TMB infestation in cashew plants, which will help in the effective management and control of pests. The study results highlight significant enhancements in both accuracy and efficiency compared to conventional severity-level classification methods.**

***Keywords*—cashew plant, Tea Mosquito Bug (TMB), infestation, labelimg, YOLOv5, mean Average Precision (mAP)**

I. Introduction

India's cashew crop (*Anacardium occidentale* L., Anacardiaceae) is a significant contributor to the country's foreign exchange earnings. Introduced by Portuguese explorers from Brazil in the sixteenth century to prevent soil erosion, cashew cultivation faces substantial losses due to infestations by the Tea Mosquito Bug (TMB), a major sucking pest [1]. TMB infestations can lead to yield losses of up to 40–50%, particularly during the flushing, flowering, and fruiting season from November to February [2]. Adult TMBs are slender and elongated, characterized by a reddish/brownish/blackish thorax and a black and white abdomen (Figs. 1 and 2).

Fig. 1. TMB insect.

Fig. 2. Different species of TMB [3].

The Helopeltis species pose a significant threat to plant health and agricultural productivity. They lay tiny, elongated eggs in various plant tissues, which hatch into nymphs in 6–8 days and mature into adults after passing through five instars in 8–14 days. Pest activity peaks in December and January, persisting until May, leading to damage to three to four shoots or panicles per insect, resulting in reduced yield. Both nymphs and adults feed on sap from tender plant parts, causing water-soaked lesions to develop within minutes, turning noticeable within hours and eventually scabby black within days. These lesions merge and contribute to the drying out of affected shoots [4].

A notable progression is signified using deep learning methodologies in the field of precision agriculture research over the past few years. The assessment of pest/disease identification of plant or plant leaves was done by several investigations based on image analysis [5, 6]. Different machine learning and deep learning algorithms that aid plant pest/disease detection in precision agriculture were reviewed [7]. The YOLOv5 deep learning algorithm, which enables the accurate

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detection of diseases in plants, can be utilized to streamline and enhance pest/disease detection procedures. This data assists farmers in making informed decisions about fertilization, and crop management practices tailored to different levels of severity of diseases [8, 9].

Using advanced image analysis techniques and the YOLOv5 deep learning object detection algorithm, this research work aims to contribute a robust and feasible model to the challenges of TMB infestation in cashew plants, offering improved accuracy and scalability for enhanced agricultural practices. YOLOv5 was designed specifically for better detection of small objects [10]. Leveraging this specific capability of YOLOv5, a pre-trained model is proposed for training the cashew plant shoot dataset. The detection of severity levels of TMB infestation in cashew plants using YOLOv5 has a broad impact on agricultural practices, improving precision, and efficiency, while also aiding in strategic decision-making for farmers in managing their yields. The proposed method will detect the infestation on plant shoots and classify the severity from healthy to severe level for regulating the application of pesticides.

II. Related Works

Drones and edge computing can give farmers access to real-time data and insights that will enable them to make better decisions, which will ultimately increase productivity, lower costs, and increase efficiency. Kumar and Murugan [5] state that their study could identify the healthy leaves with 99% accuracy and the anthracnose with 95% accuracy. Sudha *et al.* [6] examined several techniques for classifying and segmenting cashew leaf images. They showed that, the K-Means classifier combined with the Random Forest classifier outperformed the other segmentation techniques, obtaining an accuracy of 96.7%. Banana leaf diseases such as Sigatoka and Leafspot, along with healthy leaves were identified and classified using machine learning and deep learning techniques, namely k-Nearest Neighbor (KNN), Support Vector Machines (SVM), Alexnet, VGG19, ResNet50, DenseNet201, and MobileNetV2 [11, 12]. Using different techniques within the YOLO framework, Sorbelli *et al.* [13] automated Halyomorpha Halys pest scouting in orchards by utilizing RGB cameras, drones, and Machine Learning (ML) algorithms. They developed automated decision-making techniques for managing and monitoring pest insects. Yang *et al.* [14] presented Maze-YOLO, a new high-precision and real-time method for detecting pests in maize. It performed better than the state-of-the-art YOLO family of object detection algorithms at 76.3% mAP and 77.3% recall. Li *et al*. [15] conducted a comprehensive evaluation of the YOLO-JD architecture, comparing it to various state-of-the-art methods. Their results demonstrated that YOLO-JD outperformed all other methods, achieving the highest detection accuracy with an average mAP of 96.3%.

Lippi *et al.* [16] developed a YOLOv4 pest detection model intending to identify true bugs on adhesive traps within a crop field. Verma. *et al.* [17] employed three widely recognized object detection algorithms, YOLOv3, YOLOv4, and YOLOv5, for insect identification in soybean crop fields. Their findings indicate that YOLOv5 achieved the highest insect detection accuracy with a mAP of 99.5%. Liu and Wang [18] introduced an improved YOLOv3 algorithm for the detection of tomato diseases and insect pests, and they attained an accuracy of 92.3%. Tageldin *et al.* [19] proposed the machine learning algorithm XGBoost, which has proven to be the most effective method for predicting cotton leafworm infestation in greenhouses, achieving an accuracy of 84%. Chandy [20] introduced a precision agriculture technique for detecting various pests in coconut trees, employing the Nvidia Tegra System on Chip along with a camera-equipped drone. Information such as pest infestation, yield prediction, precision fertilizer application, precision irrigation, and more were then transmitted to the smart devices of agriculturists. An improved YOLOv5 was proposed by Huang *et al.* [8]. to detect small objects in mAP@0.5 with 95% accuracy. Chen *et al.* [9] improved the plant disease identification model, which was developed from the YOLOv5 network model, and was applied to identify diseases in the complex natural environment. The improved version of YOLOv5 outperformed the original by 5.4%. Egi *et al.* [21] proposed a method that uses drone footage of the greenhouse to count the number of red and green tomatoes as well as the number of flowers with an accuracy of 0.618 at mAP 0.5 using YOLOv5. Plant leaves were classified as healthy or unhealthy with an accuracy of 82.38% and latencies of 2–3 s using YOLO by Ponnusamy *et al.* [22]. Much more effectively than other well-known techniques, tassel was discovered in RGB UAV (Unmanned Aerial Vehicle) imagery using enhanced YOLOv5, which had a mAP value of 44.7% [23]. The YOLOv5 network model algorithm was used in the work of Karakaya *et al*. [24] to recognize and classify five different diseases in tomato leaves with 92.96% precision. This algorithm produced faster and more accurate results than earlier iterations of YOLO.

Mekhalfi *et al.* [25] conducted a comparative study between Transformer, EfficientDet, and YOLOv5 for crop circle detection in remote sensing imagery. They discovered that YOLOv5 was able to detect a greater number of objects than the other two. Mathew *et al.* [26] identified the ball pepper plant leaf bacterial spot disease using YOLOv5 and mAP 90.7%. Bounding boxes can be used to classify objects that appear on the road into the appropriate groups, according to the work of Sarda *et al.* (mAP 74.6%) [27]. Dai *et al.* [28] proposed a model to detect and grade the sprouted potatoes with an accuracy of 90.14% and mAP of 88.1% using improved YOLOv5 model training. To boost productivity, Ahmad *et al.* [29] developed a model that uses the YOLOv5 algorithm to classify and identify insect pests that damage crops. Additionally, they proposed a 98.3% accurate automatic system in the form of a smartphone. Ma *et al.* [30] used an enhanced YOLOv5 model to detect the lotus seed pods, and the results showed a 0.7% increase in accuracy over the traditional YOLOv5s model. YOLOv5 was used in mango detection and size estimation in the research work and reported a mean absolute error of 1.5 [31]. Yong *et al.* [32] utilized a publicly available dataset from the AI Challenger Competition in 2018, comprising 27 images depicting various diseases across 10 different crops. Employing convolutional neural networks, they achieved an impressive overall recognition accuracy of 86.1%.

The literature indicates the widespread application of the YOLOv5 architecture across various domains, consistently demonstrating high accuracy in object detection. Consequently, this study proposes the development of a model for the detection and classification of severity levels using YOLOv5 by examining lesions on plant shoots. RGB photographs of these lesion areas are captured using a DSLR camera and incorporated into the dataset.

III. Methodology

A new dataset is created from images of cashew plant shoots of the Research Centre, Kerala Agricultural University, Thrissur, Kerala, India in this work for detecting the severity of TMB infestation in cashew plants. The YOLOv5 deep learning architecture is used to train the dataset and evaluate the level of infestation severity. The proposed model is depicted in Fig. 3.

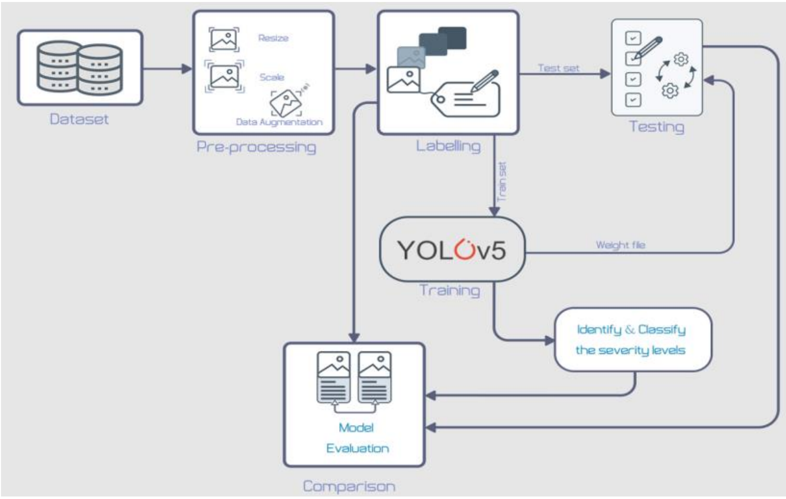

Fig. 3. Block diagram of the proposed model.

A. The Dataset

The dataset includes RGB images of both healthy and infested cashew plant shoots. All the images are captured from the Research Centre, Kerala Agricultural University, Mannuthy, Thrissur, Kerala, India. When creating a dataset, various tools such as digital cameras and smartphones are employed to gather images within the orchard. The images are collected over a period of 3 years. The dataset contains 5,626 images and 11,913 labels of 5 severity levels after data augmentation. The dataset contains images from the month of December and January of 3 years. The quality of the dataset directly impacts the accuracy of the model and its ability to identify the severity level of the infestation. This necessitates preprocessing the collected dataset.

The Kerala Agriculture University Research Center, Mannuthy, Kerala, India, the source of the data for this work, typically collects data manually from December to January. From each plot, four plants and 52 shoots are selected. An analysis is conducted on these 52 shoots, and readings are taken to determine the infected area, which ranges from 0 to 4. According to the scale followed, 0 represents a healthy shoot, 1 denotes mild infestation, 2 indicates moderate infestation, 3 signifies severe infestation, and 4 represents an extreme level of infestation. Based on these values, the agricultural researchers prepare a table of information from which a decision is made on the application of pesticides, which formulates the ground truth for this work. Different levels of lesions are depicted in Fig. 4.

(a) (b) (c) (d) (e)

Fig. 4. Different severity level images of TMB infestation of cashew plant shoots, (a) Healthy-0, (b) Mild-1, (c) Moderate-2, (d) Severe-3, (e) Extreme-4.

B. Pre-processing

Image scaling, image size equalizing, and data augmentation are the preprocessing techniques applied to image datasets. Because each image varies in size, all images are resized to a uniform 640×640 dimensions. Zooming, rotating, flipping, and clipping data augmentation techniques are applied in each image and these techniques help prevent overfitting of the model. The dataset is labeled using the labeling tool and ensures that the labels are distributed uniformly across each class. The classes are named Healthy, Mild, Moderate, Severe, and Extreme based on the severity of the infestation. The shuffled dataset is divided into three folders, training, validation, and testing, with proportions of 80%, 10%, and 10%, respectively.

C. YOLOv5 Training

The YOLOv5 architecture, introduced by Redmon *et al.* [9] yields precise object identification results. According to Redmon, object recognition is approached as a regression problem in one-level object recognition architectures. YOLOv5 developed CSPDarknet as its backbone architecture by integrating the Cross-Stage Partial Network (CSPNet) into Darknet. This algorithm ensures consistent measurements by reducing variances caused by human error.

In this work, YOlOv5, the cutting-edge real-time object detector, is used to train the cashew plant image dataset. It simultaneously determines the bounding box's coordinates and the class probability on the input image, utilizing Python's PyTorch library. Each class is balanced by adjusting the number of labels to achieve better results. The pre-trained model is used to train the dataset with image size 640 and batch size 16. The model is trained for 100 epochs to fine-tune and optimize the weights. The model's output consists of a bounding box that delineates the location of the lesion, along with a label and the associated confidence score for a specific class. The training and validation results, including the confusion matrix and performance graph, are illustrated in Figs. 5 and 6. The samples of the training and validation images are depicted in Fig. 7. Following training, the test set is employed to evaluate the model's performance. Subsequently, the label and confidence score of the bounding box around the lesion are determined.

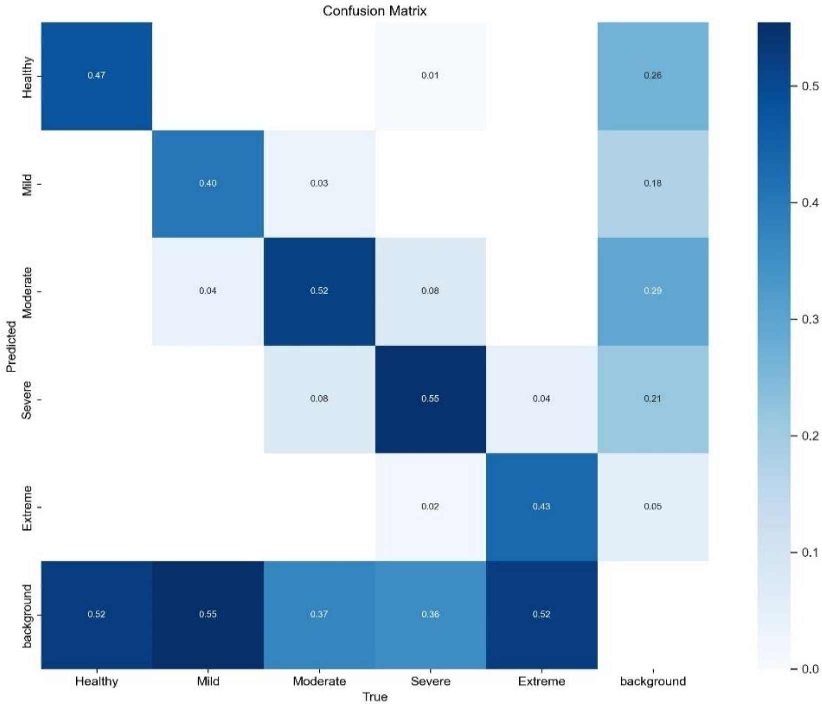

Fig. 5. Confusion matrix.

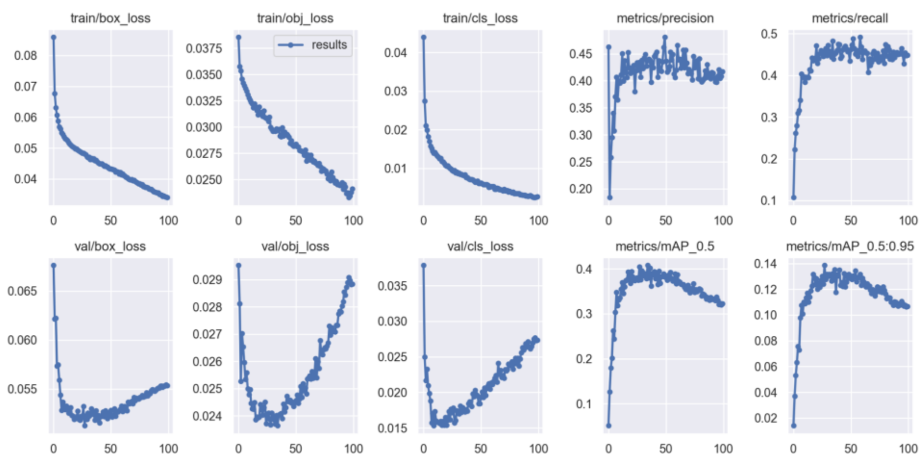

Fig. 6. Results during training.

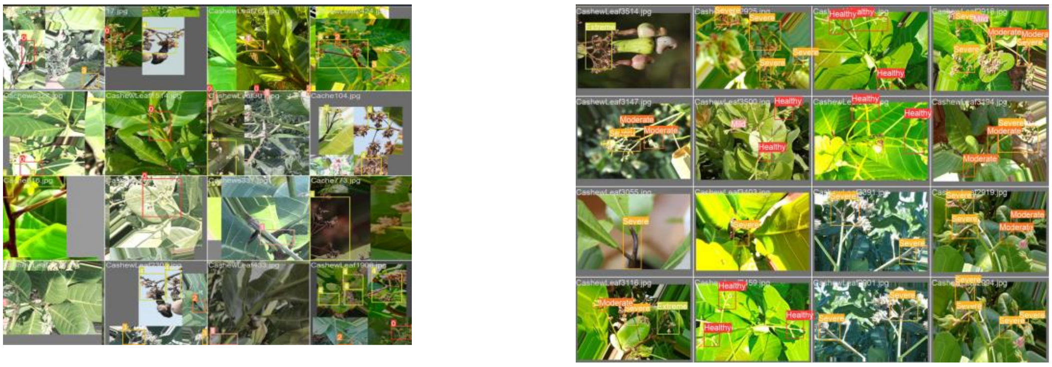

Fig. 7. Training batch and Validation batch images.

IV. Results and Discussion

The YOLOv5 algorithm is primarily employed for training the dataset. In object recognition methods, the model's performance is primarily evaluated based on the detection results and the classifier's effectiveness. Detection accuracy metrics, encompass measures like Intersection over Union (IoU), and mAP at different IoU thresholds (e.g., mAP@IoU = 0.5 and mAP@IoU = 0.5:0.95). Evaluation criteria such as precision, recall, and the F1−Score are also employed in this assessment. The IoU is a ratio computed by intersecting the actual and predicted boxes and then dividing it by their union Eq. (1).

$$IoU = \frac{Area\ of\ overlap\ of\ actual\ and\ predicted\ box}{Area\ of\ union\ of\ actual\ and\ predicted\ box} \tag{1}$$

The mAP of the model can be calculated using Eq. (2) and the model achieved 92.6% mAP@50.

$$mAP = \frac{\sum AP_k}{n} \tag{2}$$

where AP is the average precision and $n$isthe number of classes.

The training process may take some time without a GPU, but it significantly optimizes GPU utilization. This paper presents a multi-scale image-based detection method for varying sizes of infestations in various phases of plant growth. The experimental results show that YOLOv5 performs well in terms of object detection, training accuracy, and testing accuracy. The training model underwent testing using a separate testing dataset, and the outcomes are depicted in Fig. 8, showcasing sample results along with severity levels and confidence scores. The confidence score, represented as a percentage, signifies the likelihood of the algorithm accurately detecting the image. Calculated via a logistic regression function, this confidence score relies on the IoU metric between the predicted bounding box and the ground truth bounding box Eq. (3).

$$Confidence\ Score\ =\ Probability\ Pr(Object) \times IoU \tag{3}$$

Fig. 8. Test results.

The precision, recall, and F1-Score matrices for each class are evaluated, with the Severe class label demonstrating the highest precision, recall, and F1-Score at 94.2%, 93.8%, and 90.7%, respectively. Overall, the precision across all classes is measured at 92.6%, the recall at 90.9%, and the F1-Score at 92.4%. The Healthy class exhibits the lowest performance, primarily due to the varying tones of green and ash colors observed in the cashew flower at the shoot.

The model determines the lesion area along with the stage of infestation, which is very promising to agriculturists since it aids them in automating the manual tasks. Every infestation area is linked to the ground truth labeling box during the labeling phase.

The method proposed in this study is then evaluated against other state-of-the-art methods, and the results for various crops are outlined in Table I. Notably, the proposed method exhibits the highest accuracy compared to alternative approaches. Dataset generation involves the utilization of an RGB camera, offering a cost-effective alternative to 3D cameras and UAVs. Nonetheless, the dataset creation process may entail considerable time investment. Once the dataset is established and training is finalized, the model becomes applicable for identifying pest infestations in crop images. he YOLOv5 deep learning algorithm emerges as particularly effective in accurately detecting and assessing the severity of infestation.

TABLE I. ACCURACY COMPARISON OF DIFFERENT STATE-OF-THE-ART METHODS WITH PROPOSED METHOD

Sl. No.	Authors	Object	Infestation Identification Method	mAP
1	Tageldin *et al.* [19]	Cotton Leafworm	XGBoost Agorithm	84%
2	Liu and Wang [18]	Tomato Pests	Improved YOlOv3	92.39%
3	Lippi *et al.* [16]	Hazelnut	YOlO-based CNN	92.51%
4	Yang *et al.* [14]	Maize Pest	Maize-YOLO	76.30%
5	Ai *et al.* [32]	Crop Diseases	Convolutional Neural Network	86.10%
6	Proposed Method	Cashew Shoot Infestation	YOlOv5	92.60%

V. CONCLUSION

This paper offers a promising and efficient approach to address the problem of TMB infestation in cashew plants. By employing the YOLOv5 model, this automated system offers a reliable and accurate method for diagnosing the severity levels of TMB infestation. This technology has the potential to significantly aid cashew farmers in identifying and addressing TMB-related problems, ultimately contributing to increased yield and reduced losses in cashew production. The accuracy of the model improves as the dataset size grows, demonstrating a positive correlation between dataset size and accuracy. Additionally, image preprocessing and data augmentation techniques further contribute to enhancing the model's accuracy. The use of manual data collection by Agricultural University researchers can be significantly enhanced by adopting this automated model system, which will assist them in gathering data and applying pesticides more efficiently.

In the future, implementing background removal techniques for the images is likely to significantly enhance the accuracy of the model. Further research and performance analysis on the lesions can also guide farmers to determine the quantity of medicine to be applied thereby contributing to smart agriculture. This implementation may enhance the practicality and effectiveness of this innovative solution for the agricultural sector.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

The curation of the data collected from Kerala Agricultural University, Mannuthy, Kerala, India was done jointly by N. P. Vidhya and R. Priya, then they conducted the formal analysis of data, the preliminary investigation developed the methodology, utilized necessary software and resources for this research work; both authors had approved the final version.

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