



Multi-Disease Recognition in Tea Plants By Evaluating the Performance of Yolo Models

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Abstract

This work explores the innovative application of integrated pest management (IPM) strategies in the control of the Tea Looper Caterpillar and the Tea Leaf Hopper, utilizing the YOLO algorithm for real time pest detection. IPM is essential for sustainable agriculture, aiming to reduce chemical pesticide usage through a combination of biological, cultural, and technological methods. The combination of artificial intelligence and machine learning into IPM practices has shown promising results, particularly in identifying and monitoring pest populations in tea plantations. This study reviews existing literature on the impact of various pests on tea crops and highlights the significance of using advanced algorithms for effective pest management. Notably, the implementation of the YOLO algorithm demonstrated an impressive accuracy rate of 97% in detecting these pests, displaying its potential to enhance pest control efforts. By focusing on the tea green leafhopper and looper caterpillars, the research aims to provide insights into sustainable pest control methods that minimize environmental impact. The findings underscore the potential of AI-driven technologies in enhancing agricultural productivity while promoting ecological balance. This project ultimately contributes to the ongoing discourse on sustainable agricultural practices and the role of technology in addressing pest-related challenges in tea cultivation.

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1. Introduction

The tea industry significantly contributes to the economy of many countries, including India, China, Sri Lanka, and Kenya [1]. The tea sector in India is of utmost importance, both in the fields of economics and culture, with an annual revenue exceeding ₹70–100 billion. India, as the world's second-largest tea grower, makes a significant contribution to the global tea industry. The tea sector sustains a workforce of over two million individuals, mostly active in the rural areas of Assam, West Bengal, Tamil Nadu, and Kerala, which are generally characterized by economic underdevelopment. The tea production in India during the fiscal year 2022–23 amounted to nearly 1,374.97 million kilograms, indicating consistent growth compared to the preceding year. Exports are of utmost importance, as Indian tea is much desired in worldwide tea markets. The year 2023 had a valuation of around USD 818 million for tea exports originating from India, primarily targeting significant markets such as Russia, Iran, and the UAE. Black tea is the predominant variety in tea exports, accounting for almost 96% of the cumulative tea exports. The sector is intricately integrated with the Indian economy, making a big contribution to foreign exchange profits and generating considerable money for the government [2]. The quality and quantity of tea produced are closely connected to the specific characteristics of different tea varieties. Diseases and pests present a major challenge to the growth and health of tea plants, often resulting in lower yields and reduced quality.

Therefore, it is crucial to effectively tackle these challenges. While Integrated Pest Management (IPM) strategies can be beneficial, they also come with certain limitations [3]. This research seeks to explore both the advantages and drawbacks of traditional pest monitoring methods. By harnessing the power of artificial intelligence, we propose a smart model designed to overcome these limitations. Our approach seeks to deliver quick, accurate, and intelligent identification of tea diseases and pests within the intricate environment of tea plantations. This progress opens the door to more sustainable and efficient ways of producing tea. Even so, the tea corporate encounters significant obstacles posed by diver's pests that threaten both the productivity as well as quality of tea plantations. Both the tea looper caterpillar complex (*Buzura suppressaria*, *Hyposidra talaca*, *Hyposidra infixaria*) and the tealeaf hopper (*Empoasca flavescens*) are considered highly problematic pests. These insects are well known for their enormous destructive power, resulting in significant economic damage and demanding significant pest control measures [4].

1.1. Tea Looper Caterpillar complex

The tea looper caterpillar complex (*Buzura suppressaria*, *Hyposidra talaca*, *Hyposidra infixaria*) has been identified as a significant pest affecting tea crops in India. However, the black inchworm, *Hyposidra talaca* (Walker) has gained significant recognition as a defoliator over the past decade in northeast India [5]. Complete metamorphosis is the name given to the amazing process by which the tea looper caterpillar changes into four different stages: the egg, larva, pupa, and adult moth. The life cycle starts when adult moths delicately lay their eggs on the underside of tealeaves. This clever choice helps protect the eggs from predators and harsh environmental conditions. Once the incubation period is completed, the eggs hatch into larvae. This larval stage is particularly significant and challenging for tea growers and tea industries because the tea looper caterpillars feed voraciously on the tea plant's tender leaves. These larvae are the most destructive stage of the life cycle, causing extensive damage as they consume the foliage. The larvae pass through several developmental phases known as instars over a period of 15–20 days. At various developmental phases, they undergo numerous skin shedding to adapt to their expanding bodies. Their feeding pattern could end in leaf stripping, causing significant defoliation. This defoliation not only reduces the plant's photosynthetic capacity, impairing its growth and productivity, but it can also lead to reduced yields and lower-quality tea leaves. After the larval stage, the caterpillars transition to the pupal stage. During this period, which lasts about 10–14 days, the caterpillars undergo a transformation within a protective cocoon or pupal case. Inside this case, the larval structures break down and reorganize into the adult form. This stage is crucial for the development of the moth's wings, reproductive organs, and other adult features. Finally, adult moths emerge from the pupae, completing the cycle. These adult moths will then seek out mates and continue the process by laying eggs, thus perpetuating the species. The entire life cycle can change quite a bit based on environmental factors like temperature and humidity. When it is warmer and more humid, the tea looper develops faster, but in cooler and drier conditions, its growth tends to slow down. Understanding these environmental influences is critical for managing and controlling the *Ectropis obliqua* population on tea plantations.

1.2. Tea Leaf Hopper (Jaasid)

There are differences between this type of metamorphosis and total metamorphosis, which has four stages: the egg, larva, pupa, and adult. The female tealeaf hopper starts her life cycle by laying her eggs inside the host plant's leaf tissue. The female tealeaf hopper starts her life cycle by laying her eggs inside the host plant's leaf tissue. The life cycle of the tealeaf hopper begins when the female inserts her eggs into the leaf tissue of host plants. These eggs remain embedded in the leaf for a period of 7–10 days before hatching [5]. Upon hatching, the young nymphs emerge; resembling miniature versions of the adult leafhoppers but lacking fully developed wings. These nymphs immediately start to consume the plant sap by piercing the leaf tissue with their mouthparts. This feeding is crucial for their development and growth. The nymphal stage is divided into five distinct stages, or instars, that the nymphs pass through over a period of 2–3 weeks. During each instar, the nymphs molt, shedding their exoskeletons to allow for further growth. Throughout these stages, the nymphs continue to feed voraciously on plant sap, which provides the necessary nutrients for their development [6]. The feeding behaviour of both nymphs and adult leafhoppers involves piercing the leaf tissue and sucking out the sap. This feeding activity causes significant damage to the plants, manifesting as leaf curling, yellowing, and, in severe cases, necrosis, or the death of leaf tissue. Such damage not only reduces plant vigor and productivity, but also creates entry points for plant pathogens, increasing the risk of disease transmission. Once the nymphs have completed their development through the five instars, they molt into adults. These adult leafhoppers are fully winged and capable of flight, which allows them to disperse and find new host plants. Adults continue to feed on plant sap, perpetuating the damage initiated by the nymphs. Additionally, adult leafhoppers are responsible for reproduction, laying eggs, and thereby sustaining the population and infestation cycle. Adults typically live for several weeks, during which time they may reproduce multiple times, ensuring the continued presence of *Empoasca vitis* in the environment [7].

1.3. Infestations and Yield Loss

Infestations by the tea looper caterpillar and the tealeaf hopper can lead to substantial yield losses, severely affecting both the quantity and quality of tea produced.

1.3.1. Tea Looper Caterpillar Infestation

The damage caused by tea looper caterpillar larvae is primarily due to their feeding on the leaves of the tea plants. Heavy infestations can lead to severe defoliation, which reduces the photosynthetic area of the plant, thereby decreasing the plant's overall productivity. The loss of foliage can result in stunted growth and a significant reduction in the number of harvestable shoots. In some cases, severe infestations can cause entire sections of a plantation to become unproductive, requiring extensive replanting efforts. Additionally, the presence of caterpillar frass (excrement) on the leaves can degrade the quality of the harvested tea, further reducing its market value [8].

1.3.2. Tea Leaf Hopper Infestation

The tealeaf hopper causes damage primarily through its feeding activity, which involves piercing the leaf tissue and extracting sap. This feeding behaviour results in characteristic symptoms such as leaf curling, yellowing, and the formation of necrotic spots. Over time, this damage can lead to a reduction in the photosynthetic capacity of the plant, weakening it and making it more susceptible to other stresses. The indirect effects of leafhopper feeding include the transmission of plant pathogens, which can exacerbate the decline in plant health and productivity. The cumulative impact of tealeaf hopper infestations includes reduced yield, lower leaf quality, and increased susceptibility to other pests and diseases [9].

1.4. Direct Economic Losses

The direct economic losses attributable to these pests arise from the reduction in both the quantity and quality of the tea harvest. Infested plants produce fewer harvestable shoots and the leaves that are harvested are often of lower quality due to the feeding damage and contamination with frass or honeydew. This reduction in yield and quality translates directly into lower revenues for tea producers. In severe cases, entire plantations may suffer significant yield declines, necessitating costly interventions such as replanting or the application of intensive pest control measures [10].

1.4.1. Indirect Economic Losses

Indirect economic losses include the costs associated with pest management. Tea producers worldwide spend substantial amounts on the application of chemical insecticides, biological control agents, and labor for manual pest removal. The reliance on chemical control methods can lead to additional costs related to environmental monitoring and compliance with regulations aimed at reducing pesticide residues in the final product. Furthermore, the degradation of tea quality due to pest damage can lead to lower market prices, reducing profitability for farmers. Smallholder tea growers, who often lack the resources for comprehensive pest management, are particularly vulnerable to these economic pressures. The economic losses also ripple through the supply chain, affecting processors, exporters, and ultimately, consumers [11].

1.4.2. Economic Loss Worldwide

Globally, the tea industry also suffers from the economic impacts of Tea Looper Caterpillar and Tea Leaf Hopper infestations. Countries like China and Sri Lanka, which are major tea producers, experience similar challenges. The global tea market, valued at billions of dollars, sees fluctuations in supply and pricing due to pest-induced yield reductions. Furthermore, the costs associated with pest control measures and the development of pest-resistant tea varieties contribute to the economic burden on the industry [12].

1.4.3. Integrated Pest Management Strategies

Effectively managing the Tea Looper Caterpillar and Tea Leaf Hopper requires a holistic approach to pest control that brings together various methods. This means using a mix of chemical treatments, natural predators, and farming practices to keep these pests in check. Chemical control involves the judicious use of pesticides to minimize environmental impact and resistance development. Biological control leverages natural predators and parasitism to reduce pest populations. Cultural practices, such as regular monitoring, removal of infested plant parts, and maintaining optimal plant health through proper agronomic practices, are also vital components of IPM [13].

1.4.4. Implementation of Innovative Integrated Pest Management

The global agricultural sector encounters substantial obstacles arising from economic, environmental, and demographic forces, necessitating the imperative of enhancing productivity to satisfy the demands of an expanding population. India, a leading agricultural powerhouse, ranks second in the cultivation of vital crops like sugarcane, rice, cotton, and wheat. Its agricultural sector employs 60% of its workforce and contributes 17% to the GDP.

Nevertheless, Indian agriculture faces significant challenges in terms of productivity, falling behind other emerging nations by 30-50%. These challenges come from a range of factors, including insect issues, diseases, soil health, water shortages, and climate change [14]. The combination of attention processes and machine learning (ML) has great promise for addressing the problems associated with plant disease identification. ML and deep learning techniques can effectively detect agricultural illnesses by analysing images of plant parts like leaves, stems, and fruits, with poor health being visible as noticeable changes in appearance. Researchers, real-world photographs frequently feature, using diverse techniques to create an image that demonstrates characteristics commonly associated with disease. These methods serve biological purposes, enhancing our understanding of plant health. Since the emergence of deep networks, these techniques have been increasingly embraced in diverse fields [15].

In domains including speech recognition, computer vision, and natural language processing, attention approaches have proven remarkably effective. They enable models to focus on important parts of an image, which significantly improves their ability to make decisions. In the realm of computer vision, these techniques enhance a variety of applications, such as breaking down images into meaningful parts, identifying objects, classifying images, and generating captions for pictures [16]. Integrated Pest Management (IPM) is a well-rounded strategy for dealing with pests that brings together different methods. Its goal is to cut down on the use of chemical pesticides and promote more sustainable farming practices. In the case of the tea looper caterpillar and the tealeaf hopper, two significant pests in tea cultivation, innovative IPM strategies are essential to maintain crop health and productivity [17]. This work aims to improve both model performance and understanding by providing a thorough analysis of attention mechanisms and their impact on plant disease diagnosis. The study will investigate how these mechanisms contribute to feature extraction and improve disease detection accuracy. This study offers a comprehensive examination of attention mechanisms and their influence on diagnosing plant diseases, focusing on enhancing both model performance and understanding. A cutting-edge method currently being utilized is the YOLO - (You Only Look Once) algorithm, which is a leading framework for detecting objects.

The YOLO target identification method is well recognised for its relatively small model size and fast processing speed, which allows for real-time object detection, even in video streams. YOLO's simple design enables it to independently generate bounding box coordinates and categories from a single network iteration, using global picture characteristics to reduce mistakes in detecting backgrounds and improve its ability to generalise to various domains. The YOLO model converts target detection into a regression issue, enabling rapid processing. However, its accuracy, especially when dealing with objects that are in close proximity or in clusters, may be inferior. This constraint stems from the prediction of just two bounding boxes per grid cell, leading to subpar performance when dealing with atypical aspect ratios and limited generalisation. An optimal loss function design is crucial for achieving a balance between localisation accuracy, especially for objects of varying sizes, and enhancing the overall efficiency of detection. The YOLO framework is built with 24 convolutional layers, succeeded by two fully connected layers. Each grid cell is evaluated to predict several bounding boxes, and the most accurate box is selected via non-maxima suppression based on Intersection Over Union (IOU) with the ground truth [18].

The YOLO algorithm, renowned for its speed and accuracy, is particularly suited for real-time applications [19]. By integrating YOLO into IPM, farmers and researchers can quickly and accurately identify and quantify pest populations in tea plantations. This advanced detection capability allows for precise monitoring of pest activity and early intervention, minimizing the need for broad-spectrum insecticides and reducing environmental impact. The implementation process begins with training the YOLO algorithm on a comprehensive dataset of images that include the tea looper caterpillar and the tealeaf hopper in various stages of their life cycles and under different environmental conditions. This training enables the algorithm to recognize these pests with high accuracy. Once trained, the algorithm is deployed using drones attached to multispectral cameras that continuously monitor the tea fields. The real-time data collected by the YOLO-powered systems is then analysed to determine pest hotspots and population dynamics. This information is crucial for making informed decisions about targeted interventions, such as the release of biological control agents, the application of pheromone traps, or the strategic use of selective pesticides. By focusing control efforts on areas with the highest pest pressure, the overall use of chemicals can be significantly reduced, leading to more sustainable and environmentally friendly tea production. YOLO integration in IPM facilitates the creation of a comprehensive pest management database. This database can be used for long-term monitoring and research, helping to refine pest control strategies over time. The data also supports the development of predictive models to anticipate pest outbreaks and improve the timing of interventions. Further research into the life cycles and infestation dynamics of these pests is crucial. Understanding the specific conditions that favour pest development, such as temperature, humidity, and host plant availability, will allow targeted interventions to be developed. By identifying the critical stages in the pests' life cycles, researchers can design more effective control strategies that are both timely and precise. The innovative application of the YOLO algorithm in integrated pest management for the tea looper caterpillar and the tealeaf hopper represents a significant advancement in sustainable agriculture. By enhancing the precision and efficiency of pest detection and control, this technology helps to protect tea crops, reduce environmental impact, and promote the overall health

of the ecosystem. Mitigating the impact of tea looper caterpillars and tealeaf hoppers will not only enhance the yield and quality of tea crops, but also help secure the future of the global tea industry. This industry is vital to many countries' agricultural economies and provides livelihoods for millions of people worldwide. By ensuring the health and sustainability of tea plantations, we can continue to support these communities' economic stability and social well-being [20].

2. Related Works

This review focuses on the implementation of innovative integrated pest management strategies for dealing with the tea looper caterpillar and the tealeaf hopper, utilizing the YOLO algorithm. Integrated Pest Management (IPM) seeks to lessen the dependence on chemical pesticides by utilizing a range of approaches, including innovations in technology like artificial intelligence and machine learning. One prominent example is the YOLO algorithm, which enables real-time object detection that can be applied to monitor the tea plantation for these pests. In their study, [21] investigated the impact of three polyphagous looper caterpillars complex, such as *Buzura suppressaria* Guenée, *Hyposidra talaca* Walker, and *Hyposidra infixaria* Walker, on tea (*Camellia sinensis* L.) growing in the Terai region of sub-Himalayan West Bengal. The investigation successfully discovered *Schima wallichii* (DC.) Korth. as a viable and natural alternate host for these looper complex. The study investigated host choice, life cycle characteristics, and detoxification enzyme quantification, and to gain a deeper understanding of looper-host plant interactions. The results indicated that all looper species exhibited eating preferences caused by their hosts. The author in [22] emphasizes that the tea green leafhopper, *Empoasca flavescens* Fabricius, is a significant and persistent pest in tea plantations, which has been conventionally controlled by the widespread application of pesticides. As a reaction to the pressing requirement for more sustainable and environmentally friendly methods of pest control, his study specifically examines salivary protein studies to get a deeper understanding of the factors that trigger or trigger the interaction between leafhoppers and tea plants. The study intends to contribute to reducing pesticide dependence in the tea sector and promote more sustainable pest management protocols by investigating new regulatory targets and pathways linked to these salivary proteins.

According to [23], rapid and dependable identification of insect species is crucial for efficient pest control, animal quarantine, and the optimal use of insect resources. While conventional morphological classification approaches are characterised by their labour-intensive and time-consuming nature, machine learning (ML), which encompasses both classic machine learning (TML) and deep learning (DL), presents a viable alternative by means of automated picture identification procedures. This article delineates the procedure of automated insect identification using machine learning, encompassing phases such as capturing images, preprocessing, segmenting, identifying, and detecting. Furthermore, the review emphasizes the applications of this technology in several insect orders, including Coleoptera, Lepidoptera, Hymenoptera, Diptera, and Orthoptera. They suggest a number of areas for further research, such as making large public datasets, reducing subjective biases in photography, looking into deep learning models that can be understood, and expanding studies to include a wider range of insect species. The investigation identifies these developments as crucial for timely pest control, mitigating chemical contamination, and promoting environmental sustainability.

In their study, the author in [25] focus on the increasing demand for accurate and effective mechanisms for detecting plant diseases. Specifically, they want to overcome the difficulties presented by real-field photos, including intricate backgrounds and the simultaneous identification of several illnesses exhibiting identical symptoms. The work highlights the significance of attention processes in improving the resilience of machine learning classification models by enabling these algorithms to specifically concentrate on pertinent regions or characteristics within affected areas. This research investigates different attention techniques that are included into three different models: ShuffleNetV2, EfficientNetV2, and MobileNetV2. These mechanisms make use of transformer modules, the Convolutional Block Attention Module, and squeeze and excitation layers. The efficacy of these approaches in enhancing picture segmentation, feature extraction, object recognition, and was demonstrated by evaluating the performance of these models, which included attention modules, using various metrics. The author et al. [26] have highlighted the significance of rapid and precise identification of plant diseases in order to ensure sustainable agricultural productivity. Traditionally, recognizing plant abnormalities caused by diseases, pests, nutrient deficiencies, or extreme weather has relied on the expertise of human analysts. However, this method is expensive, time-consuming, and occasionally unfeasible. In order to tackle these difficulties, research has progressively concentrated on employing image processing and machine learning methods for the accurate identification of plant diseases. His work provides an extensive examination of recent research in this domain, placing special attention on the utilization of inexpensive and readily accessible RGB photographs. The analysis emphasizes a transition towards deep learning models as opposed to conventional shallow classifiers that rely on manually designed features. Although these models have attained commendable recognition accuracies on particular datasets, their performance frequently deteriorates when employed on novel datasets or real-world field settings. Notwithstanding these obstacles, the advancement is encouraging. The research additionally provides empirical findings that compare the performance of eleven convolutional neural network (CNN) architectures in

terms of accuracy, recall, precision, specificity, F1-score, training length, and storage requirements. His investigation provides the implementing appropriate designs in both traditional and mobile/embedded computing settings. Additionally, the authors address the current difficulties in creating realistic, automated plant disease identification systems for field applications.

The author in [27] conducted a study analyzing the detection capabilities of the YOLOv8 model and hyperparameter optimization (HPO) across four agricultural datasets, involving 20 different training scenarios. The results of the investigation showed that, with mean Average Precision (mAP) values of 0.8507 and 0.9466 for the Weed/Crop and Pineapple datasets, respectively, the YOLOv8n model obtained the highest scores. On the other hand, the YOLOv8l model performed better on the Grapes and Pear datasets, with mAP scores of 0.9641 and 0.6510, respectively. Conversely, the YOLOv8l model demonstrated superior performance on the Grapes and Pear datasets, achieving mAP scores of 0.6510 and 0.9641, respectively. These results suggest that YOLOv8n excels in detecting multiple species or objects at different developmental stages within a single species, whereas YOLOv8l is more effective in scenarios where object detection primarily involves extracting objects from a background. This study examines the substantial influence of Tephritidae pests on the quality and safety of different melons, fruits, and vegetable crops. Many agricultural managers lack enough knowledge of pest incidence levels, resulting in the improper use of pesticides, which in turn leads to environmental contamination and economic losses. The paper highlights the need of the real-time identification and quantification of Tephritidae pests to address this problem and provide efficient pest control. Based on the YOLOv8n architecture, the authors provide YOLO_MRC, a rapid and lightweight model designed to precisely target *Bactrocera cucurbitae* pests. The objective of this model is to efficiently and precisely ascertain the distribution and abundance of pests, therefore assisting agricultural management in the optimization of pesticide application. Similarly, the author in [28] focus on the need for a reliable and accurate system for detecting and managing tealeaf diseases. Traditional manual detection techniques take a lot of time and have a detrimental effect on productivity and tea quality output. Through the training of the YOLOv7 model on an image, dataset of diseased tealeaves taken from four prominent tea gardens in Bangladesh, his study presents an AI-based solution. The dataset, comprising 4,000 digitally annotated images of five different leaf diseases, is enhanced through data augmentation to address sample size limitations. Statistical metrics were employed to validate the performance of the YOLOv7 model, which yielded high results in terms of detection accuracy, precision, recall, mAP value, and F1-score (97.3%, 96.7%, 96.4%, 98.2%, and 0.965, respectively). The experimental results reveal that YOLOv7 outperforms other models such as CNN, Deep CNN, DNN, AX-RetinaNet, enhanced DCNN, YOLOv5, and multi-objective picture segmentation in detecting tealeaf illnesses in natural scene images.

According to [29], the prompt and precise identification of tea tree pests is crucial for efficient pest management. To accomplish this, they gathered a collection of 782 photos depicting eight prevalent tea tree pests, where each image had 1 to 5 distinct pest species distributed randomly. This dataset was used to build a tea garden insect detection and recognition model based on the YOLOv7-tiny network, which integrates deformable convolution, the Biformer dynamic attention mechanism, a non-maximal suppression algorithm module, and a novel implicit decoupling head. In ablation trials, the model performed quite well, averaging 93.23% accuracy. A comparison with seven popular detection models—EfficientDet, Faster R-CNN, RetinaNet, DetNet, YOLOv5s, YOLOR, and YOLOv6—achieved additional validation of the model. Ye et al. (2024) highlight the challenges associated with tea pest identification, such as low detection accuracy, false positives, false negatives, and long processing times. They propose an improved YOLOv8 approach to address these issues. His research implemented several significant enhancements: the use of lightweight convolution (SEConv) as a replacement for conventional convolution in order to decrease network parameters and improve detection speed; the addition of the SEF module, which is based on SEConv, to enhance the detection of targets at multiple scales; and the integration of the efficient multi-scale attention (EMA) module to highlight target features and effectively reduce background noise. Furthermore, a lightweight detection head was developed using the multiscale convolutional attention module (MCA) to enhance the accuracy of detection [30]. A refined variant of the Wise-IoU bounding box loss function was created with the express purpose of addressing gradient issues in the training dataset's low-quality samples. Experimental findings showed that the improved YOLOv8-SEM model surpassed the YOLOv8s baseline by a substantial margin. Specifically, precision, recall, and mAP@0.5 increased by 2.4%, 5.2%, and 2.9% correspondingly. This refined model has improved resilience, precision, and capacity to generalize, rendering it especially advantageous for multi-scale pest detection tasks in intricate environments, thereby making a substantial contribution to tea pest detection.

3. Methodology

We have created a machine-learning model leveraging artificial intelligence to tackle tealeaf infestation and diseases. Trained on a comprehensive dataset of tealeaf images, meticulously labelled looper caterpillar complex *Buzura suppressaria* Guenée, *Hyposidra talaca* Walker, and *Hyposidra infixaria* Walker and tea green leafhopper (*Empoasca flavescens*) infestation patterns. This model is equipped to identify and combat these issues. The

utilization of machine learning and image processing technology for automatic detection and identification of crop specific pest infestation and diseases has emerged as a vital approach in the automated diagnosis of crop diseases, owing to advancements in computer technology.

3.1. Data collection

The images data set collected from Tocklai Tea Research Institute (26°43'44.1"N 94°13'41.1"E), located in Cinnamara, Lichubari, Jorhat District, Assam, India, provided the data (Figure 1). The information of the infected patterns and the pest list (Table 1) gathered from Tocklai. The pest leaves that were gathered outside are arranged for image shooting and sorting in an indoor setting with natural light and fluorescent light at a temperature of 25°C, accounting for the influence of the external environment. The DJI Mavic 3 pro drone attached with multispectral digital camera, with clever focusing and an 850 x 850-pixel resolution is the shooting apparatus. The picture was taken with the blade at a distance of 25 to 35 cm, at a tilt angle between 20° and 50°C, and at 90° C perpendicular to the blade. During our study, we specifically captured 18786 pest-infested images, among those 6886 images showing leafhopper infestation, 5530 images showing looper caterpillar infestation, and 5770 uninfested healthy tealeaves.

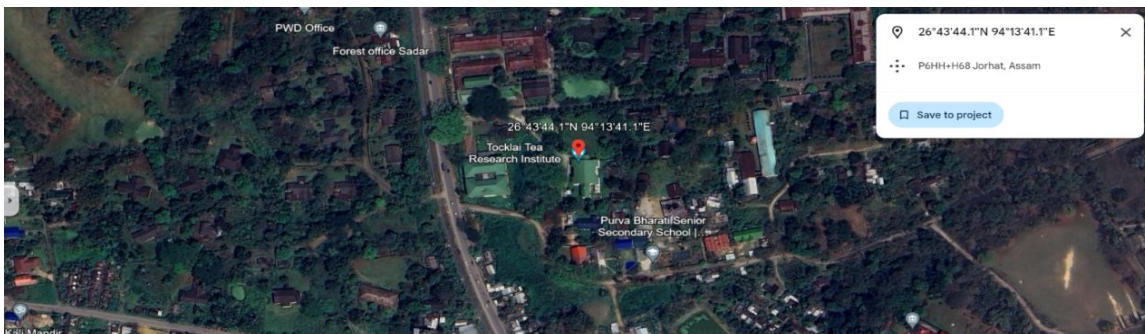


Figure 1. Study site

To improve the efficiency and speed of the model's calculations, we crop and compress the oversized areas of images while filling in any undersized parts before training and testing. As a result, the final processed image resolution is set to 224 × 224 pixels.

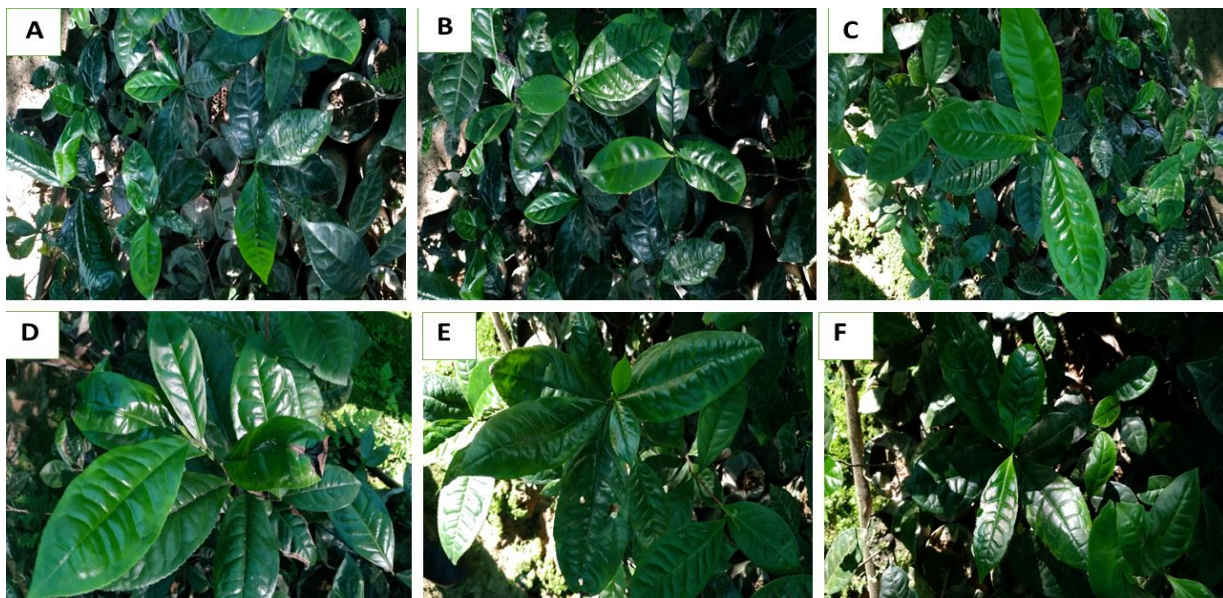


Figure 2. Damage symptoms of tealeaf hooper photo

Also called tealeaf hopper, both adults and nymphs, drain the sap of young leaves leading to uneven and downward curled leaves, the margin becomes re-curved and subsequently turns brown and dry up. This particular symptom is known as rim blight (Fig 2). The damage symptoms become quite prominent on bushes in May at the time of the second flush. The pest is more active during May-July. The population suddenly declines to a negligible number from August onwards (Fig 2).

Table 1: Monthly tealeaf hooper infestation in tea plants

S.No	Months	Mean no of jassids/tea leaf hooper
1	January	3
2	February	8.5
3	March	13
4	April	28
5	May	14
6	June	4
7	July	3.5
8	August	0.3
9	September	0.2
10	October	0.1
11	November	4.5
12	December	3.6

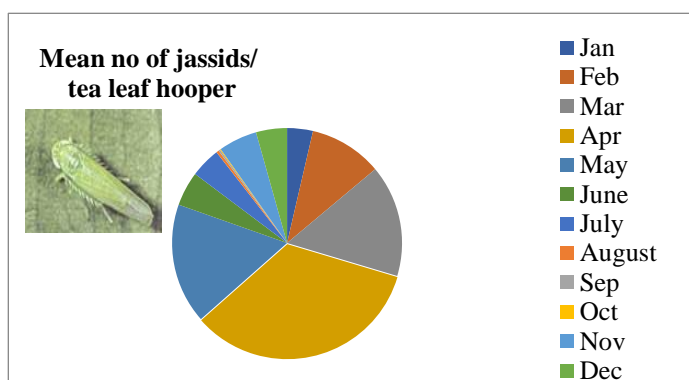


Figure 3. Monthly tea leaf hooper infestation in tea plants

The moth is grayish-white, speckled with black, and males are typically smaller than females, easily recognized by their feathered antennae. In the early larval stages, these caterpillars create holes in leaves, but as they mature, they consume entire leaves, sometimes-stripping tea bushes bare during severe infestations.



Figure 4. Damage symptoms of tea looper photo

This species is noted as one of the earliest looper caterpillars infesting tea. Females lay 200 to 600 eggs in clusters, covered in buff-colored hairs, primarily on the trunks of shade trees or tall plants nearby. Young caterpillars start dark brown with greenish-white lines, eventually turning light green and later resembling the color of mature tea twigs. After undergoing five larval stages, fully-grown caterpillars move to the ground to pupate at a depth of 2.5-5 cm beneath the tea bushes, with the pupal stage lasting around three weeks in summer and over three months in colder conditions. The entire life cycle spans about 72 days from March to May and around 60 days from June to July. The seasonal abundance and the population dynamics are presented in Fig 5.

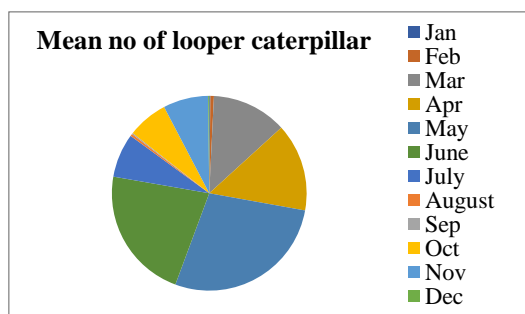


Figure 5. Dynamics of *Buzura suppressaria* population

Table 2: Monthly tea looper caterpillar infestation in tea plants

S.No	Months	Mean no of looper caterpillar
1	Jan	0.1
2	Feb	0.3
3	Mar	6.5
4	Apr	7.6
5	May	14.5
6	June	11.5
7	July	3.8
8	August	0.2
9	Sep	0.1
10	Oct	3.5
11	Nov	3.9
12	Dec	0.1

It is also known as a ‘black inch worm’. The larvae of this species are polyphagous, meaning they have a varied diet and are known to feed on a wide range of trees, shrubs, and weeds. When the caterpillars first hatch, they create tiny holes along the edges of young leaves before munching on the leaf margins. You can often find the younger caterpillars on new shoots and buds, where they scrape the surface of the leaves as they feed. (Fig 6).

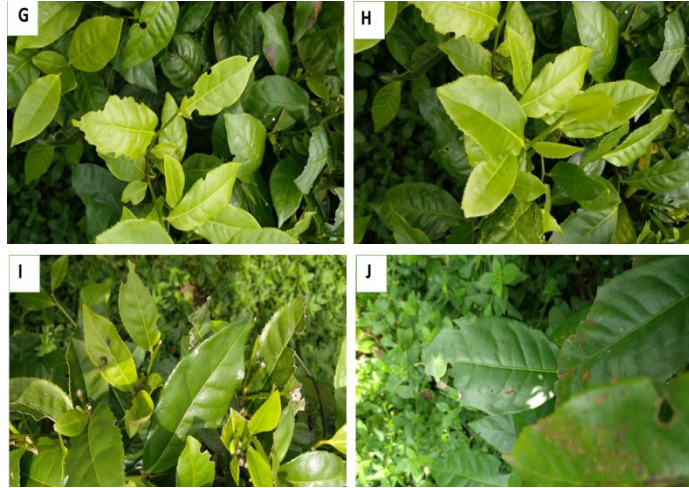


Figure 6. Damage symptoms of new tea looper photo

Occurrence of a few more species of loppers such as *H. infixaria*, *Ascotis* sp., *Cleora* sp. and *Ectropis* sp. has also been recorded from North Bengal, Upper Assam, North Bank of Assam. *Hyposidra talaca* is found to be the most dominant one among the newer species of the looper caterpillars. The seasonal abundance and the population dynamics are presented in Fig 7.

Table 3: Mean no of tea looper

S.No	Months	Mean no of tea looper, <i>Hyposidra talaca</i>
1	Jan	3
2	Feb	7.5
3	Mar	9
4	Apr	7
5	May	14
6	June	15
7	July	4.5
8	August	7.5
9	Sep	9
10	Oct	8.5
11	Nov	9
12	Dec	3.5

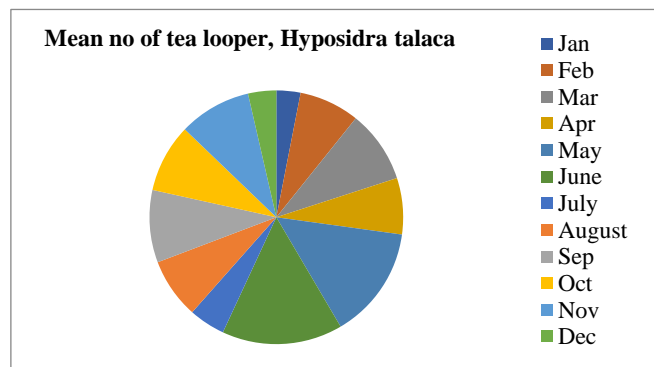


Figure 7. *Hyposidra talaca* population dynamics



Figure 8. Image data-set collection in field

3.2. Data pre-processing

Crops can be affected by a wide variety of diseases and insect pests, and their leaf sizes can vary significantly. In some cases, there may only be a handful of images available for a specific disease or pest on certain plants, without any healthy samples to serve as control groups. This lack of balanced data makes it challenging to train effectively. Therefore, it's important to optimize the dataset to ensure it's suitable for both training and testing the model.

3.2.1. Optimize the data set

To optimize the dataset, 42 subsets are picked from the produced image collection for usage as experimental sub-datasets. With these smaller datasets, which contain fewer categories and samples, the viability of the network model and the tweaking of network parameters are examined in an effort to expedite the experiment and save time in general.

3.2.2. Image transformation

For image transformation, the size of each photo is modified using interpolation to standardize them all to 224×224 pixels. During this procedure, different interpolation techniques were evaluated, and the best scaling results were obtained with the nearest neighbour interpolation technique. This method effectively preserves the distinctive shape of the leaves, along with the details of the edges and disease patterns. Figure 3(a) illustrates an image processed with bilinear interpolation, while Figure 3(b) displays the results achieved with nearest neighbour interpolation.

3.2.3. Data enhancement

The first stage in improving the data and network accuracy is to shuffle the images at random to make sure that the statistical properties of the test and training sets are similar. Next, 12 is selected as the batch size. Following these procedures, datasets that are appropriate for convolutional neural network model training can be produced. Another option is to divide the whole dataset into two halves at random: a training section and a testing section. To best balance these two dataset components, the training rate is changed.

4. Result and Analysis

4.1. YOLO Architecture

The most recent model in the You Only Look Once (YOLO) family of object identification models, which is renowned for its accuracy and speed, is called YOLOv8. Bounding boxes and class probabilities of an image are predicted by the YOLO in a single evaluation. Finding and detecting things of interest in an image is the task of object detection. The backbone of a convolutional neural network (CNN) is responsible for extracting information from the input image. YOLOv8 makes use of a unique CSPDarknet53 backbone that leverages cross-stage partial connections to increase accuracy and enhance information flow between layers. Neck: Often known as the feature extractor, the neck gathers data at various scales by combining feature maps from numerous backbone stages. YOLOv8 instead of the traditional Feature Pyramid Network (FPN) uses an innovative C2f module. Combining high-level semantic features with low-level spatial information, this module increases identification accuracy, especially for small items. Head: Forecasting is the responsibility of the head. To anticipate class probabilities, bounding boxes, and objectness scores for each grid cell in the feature map, YOLOv8 uses a variety of detection modules. The final detections are obtained by combining these projections. The table displays the available sizes of the YOLO model used in this article: nano (N), small (S), medium (M), large (L), and extra-large (xL). Notably,

from YOLO v5 to v8, the heavier versions have gotten lighter, while the lighter models have gotten heavier. More layers and parameters in heavier models allow for more accurate learning with sufficient data, but the computation durations for training and prediction are also longer. The L and xL models are advised for cloud-based use, while the S and M models are suggested for mobile applications in the developers' YOLO model guide.

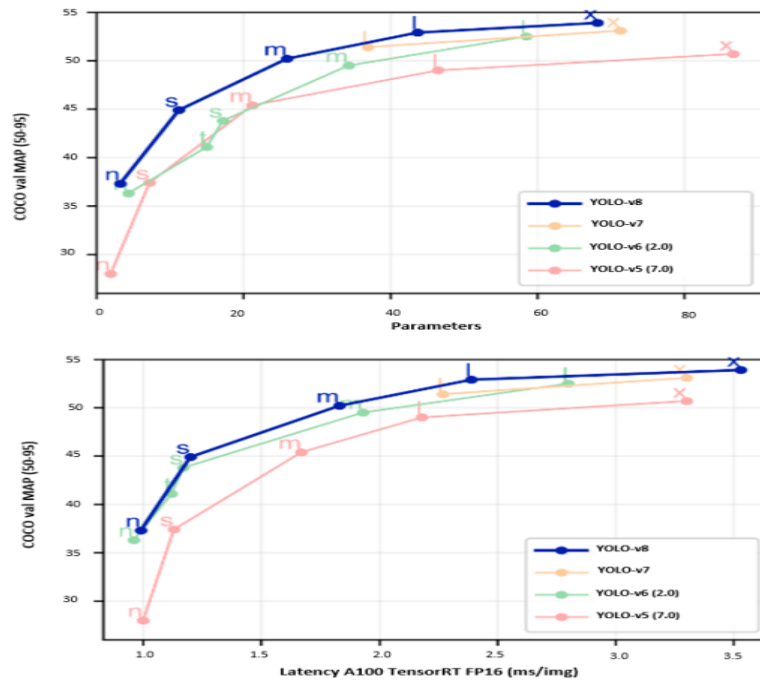


Figure 9. YOLO-v8 is compared to YOLO-v5 and YOLO-v6

Fig 9 YOLO-v8 is compared to YOLO-v5 and YOLO-v6 (Hussain, M. (2023)), which were both trained on 640 x 640 images. This comparison demonstrates that all YOLO-v8 versions achieve improved throughput while keeping a same amount of parameters. This suggests improvements to hardware-efficient architecture. In addition to YOLO-v5, which is renowned for its outstanding real-time performance, Ultralytics also offers YOLO-v8. It is quite likely that YOLO-v8 will prioritize deployment on limited edge devices with high inference speeds, based on the preliminary Ultralytics benchmarking results.

Table 8: Comparison of number of layers and parameters for each YOLO model

Category	Version	Nano	Small	Medium	Large	Extra Large
Layers	V5	214	214	291	368	445
	V8	225	256	295	365	365
Parameters	V5	1.8	7	20.9	46.1	86.2
Millions	V8	3	11.1	25.9	43.6	68.2

4.3 Working

* The input image is organized into a grid, with each grid cell responsible for predicting objects within its spatial domain.

* For every object it detects, each grid cell projects the bounding box coordinates, class probabilities, and objectness scores.

* To get rid of duplicate detections, a non-maximum suppression technique is applied to the anticipated bounding box coordinates.

* A collection of bounding boxes with the anticipated class label and confidence score in each is the result.

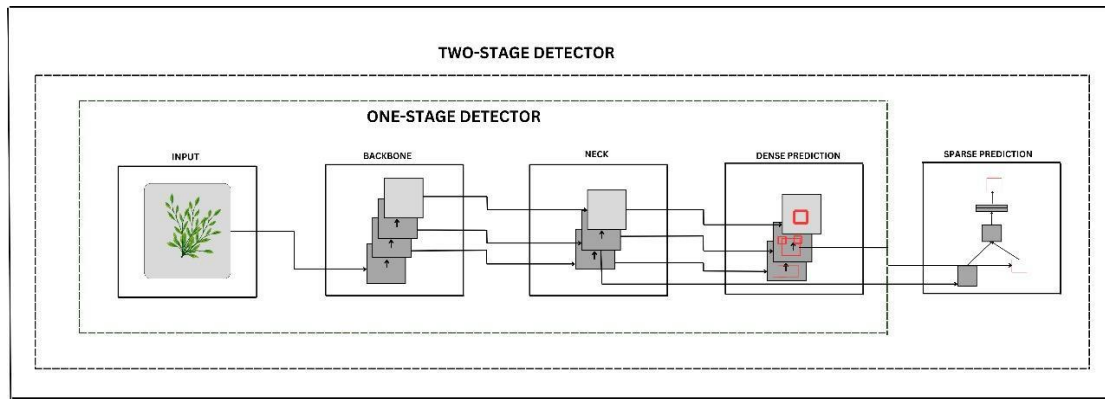


Figure 10. Schematic representation of a YOLO

For object detection, two-stage and one-stage detectors are used.

For training the YOLO model, there are about thirty user-configurable parameters. The values of these options affect the training results. We call these settings "hyperparameters." Below is a description of the hyperparameters that this study looked at. An epoch is a whole iteration of the training dataset used for learning. Underfitting may result from insufficient learning if the number of epochs is too low. On the other hand, if there are an excessive number of epochs, the training time will increase and the model may overfit the training data, which will result in subpar performance on fresh, untried data. Setting a proper epoch value that yields excellent test results and allows for adequate training is therefore crucial. However, this value cannot be ascertained until the dataset is applied. It is advised by the YOLO to begin with 300 epochs. It is recommended to reduce the number of epochs if overfitting is identified; if not, it can be increased to 600, 1200, and so on, with the learning process being continuously monitored to determine the appropriate epoch value. The amount by which the parameter values are modified in response to the loss experienced during a single learning session is determined by the learning rate (Lr). Should this value be excessively high, each iteration's loss could rise, resulting in divergence and ineffective learning? On the other hand, learning proceeds too slowly if the value is set too low. As a result, choosing a suitable Lr based on the data's properties is essential. The default initial Lr in YOLO is set to 0.01; however, the suggested initial Lr changes based on the optimizer that is used: 0.001 for Adam, AdamW, and RMSProp, and 0.01 for stochastic gradient descent (SGD), which is the default optimizer in YOLO. As training advances and the number of epochs rises, deep learning may fail to produce loss improvement at the original learning rate (Lr). This happens because the initial Lr growing to be too huge for the millions of parameters in the updated or enhanced training model may prevent any further loss reduction. In these situations, tweaking one parameter could help reduce the loss, but changing another too much could raise the loss and reduce the accuracy overall in comparison to the prior epoch. Different decay strategies have been developed to handle this problem, allowing the Lr to be adjusted as training epochs go.

The final learning rate (lrf) in YOLO is set to reduce the learning rate (Lr) by a predetermined amount in each epoch, using a linear decay mechanism by default. Thus, "final Lr (lrf)" multiplied by "initial Lr (lr0)" yields the Lr in the last epoch. Thus, the Lr declines less in each epoch if the epoch value is relatively big; on the other hand, the Lr decreases more considerably in each epoch if the epoch value is lower. Therefore, the interaction between the epochs and the lr0 and lrf values affects the correctness of the learning outcomes. Due to dataset variability, no approach currently in use can anticipate results in advance; instead, it takes a great deal of time and effort to identify and apply optimal values through numerous trials. As the number of epochs increases, the accuracy of the training data continues to improve, but the validation data accuracy—which is not considered into the learning (loss improvement) process—may plateau after a certain point. Under such circumstances, implementing an early stop condition can greatly cut down on the total amount of time needed for deep learning. A user-defined integer called the "early stop patience" indicates when training will end if validation accuracy does not increase for a predetermined number of consecutive epochs. The default level of patience in YOLO is 50 for version 8 and 100 for version 5. The weight values of all parameters from the final epoch and the epoch with the best validation accuracy are saved separately for use in testing or prediction with additional data if the early stop condition is triggered during training.

Input Image: An input image is sent to the two-stage detector's first stage.

Backbone: Next, the input image is run through the backbone, which is also referred to as a convolutional neural network (CNN). Features are extracted from the image by the backbone. The detector will effectively use these attributes as characteristics to identify things in the image.

Neck: A layer of the neck passes through the features that were taken from the backbone. Features can be fused together or dimensionality reduced by the neck layer. To produce a more complete feature representation, feature fusion integrates low-level and high-level features that were taken out of the backbone.

Region Proposal Network (RPN): The output of the neck layer is subsequently sent into a region proposal network (RPN). Region proposals, or candidate bounding boxes for possible objects in the image, are created by the RPN.

Classification and Bounding Box Regression: Next, a classifier is used to categorize each region proposal in order to ascertain whether or not an object is actually present, and if so, what rather object it is. Bounding box regression is also used to fine-tune the bounding boxes' size and location.

Output: For each object in the image that is detected, the two-stage detector produces the bounding boxes and associated class labels

The YOLOv8 model was trained for 100 epochs, with the entire training process completing in 0.418 hours. The optimizer was removed from the last.pt and best.pt weights, reducing each to a size of 22.5MB. The model was validated using a Tesla T4 GPU, with specifications as follows:

Model Architecture: 168 layers, 11,129,067 parameters, 28.5 GFLOPs

Validation Dataset: 47 images

During training, the model's performance across different classes was evaluated. The results are summarized in Table 1.

Table 9: Training Performance Metrics

Class	Images	Instances	Precision	Recall	mAP50	mAP50-95
all	47	168	0.471	0.431	0.349	0.281
RSM	47	2	1.000	0.946	0.995	0.895
TMB	47	20	0.307	0.700	0.673	0.475
TMB-insect	47	5	0.434	0.200	0.105	0.063
dry	47	23	0.172	0.261	0.158	0.121
health	47	76	0.364	0.553	0.462	0.388
insect	47	1	1.000	0.000	0.000	0.000
mother-leaf	47	36	0.327	0.389	0.262	0.172
thrips	47	5	0.167	0.400	0.134	0.133

The model's validation performance was evaluated using the same dataset. Table 2 presents the metrics obtained during validation.

Table 10: Validation Performance Metrics

Class	Images	Instances	Precision	Recall	mAP50	mAP50-95
All	47	168	0.511	0.221	0.234	0.192
RSM	47	2	1.000	0.000	0.546	0.491
TMB	47	20	0.213	0.200	0.155	0.151
TMB-insect	47	5	0.775	0.200	0.211	0.126
Dry	47	23	0.180	0.217	0.155	0.125
health	47	76	0.373	0.421	0.394	0.328

Class	Images	Instances	Precision	Recall	mAP50	mAP50-95
insect	47	1	1.000	0.000	0.000	0.000
mother-leaf	47	36	0.360	0.333	0.279	0.186
thrips	47	5	0.191	0.400	0.132	0.132

Table 11: Processing Time per Image

Phase	Time (ms) per Image
Preprocessing	0.2
Inference	5.5
Loss Computation	0.0
Post-processing	3.8

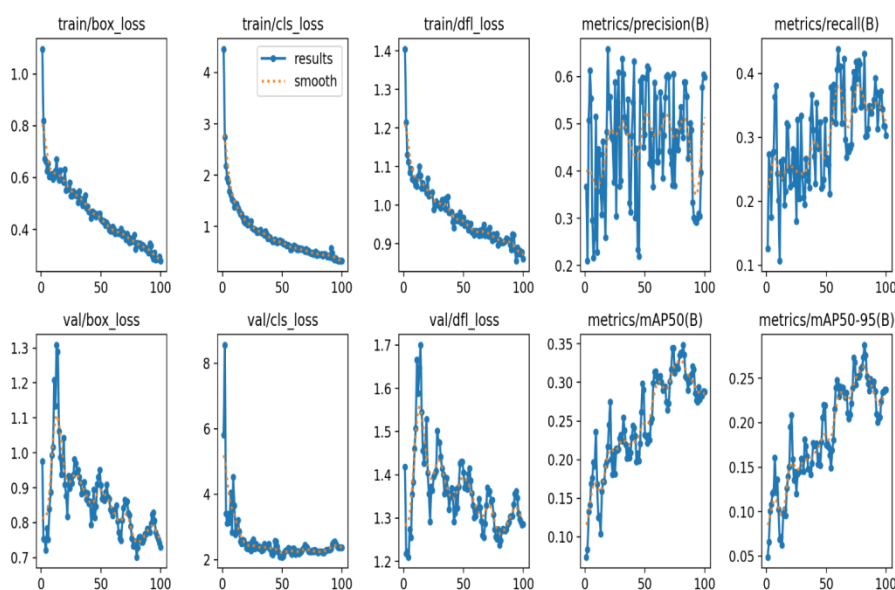


Figure 11. accuracy graph

The train/box_loss, train/cls_loss, and train/df_l_loss plots show a decreasing trend, indicating that the model is learning and improving over the epochs. The smoothing line (orange dotted) helps in visualizing the overall trend despite the fluctuations. The val/box_loss, val/cls_loss, and val/df_l_loss plots also show a decreasing trend, but with more variability compared to the training losses. This is expected as the validation set is used to evaluate the model's performance on unseen data. The metrics/precision (B), metrics/recall (B), metrics/mAP50 (B), and metrics/mAP50-95(B) plots show the performance metrics over the epochs. The precision and recall plots indicate the trade-off between these two metrics during training. The mAP50 and mAP50-95 metrics provide insights into the model's accuracy. The increasing trend in these plots suggests that the model's ability to detect objects is improving over time.

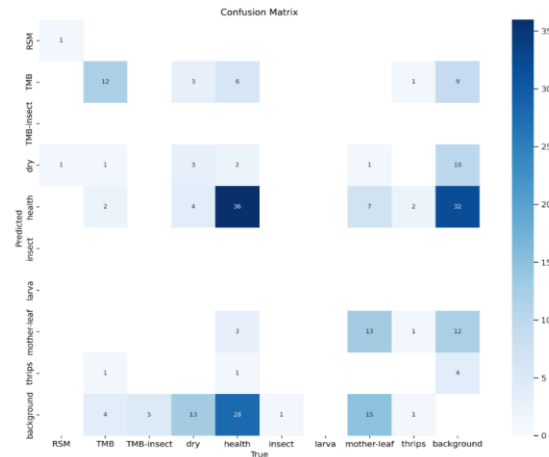


Figure 12. confusion matrix

The confusion matrix displays how many predictions the model got right and wrong for each class. The diagonal elements reflect the correct predictions, while the off-diagonal elements highlight where misclassifications occurred. Key observations include:

The model performs well in predicting the "health" class, with 36 correct predictions out of 76 instances. There are significant misclassifications between the "mother-leaf" and "health" classes, indicating that these classes may have similar features that confuse the model. The "TMB" class has 12 correct predictions out of 20 instances, with some misclassifications as "dry" and "mother-leaf." These outcomes give a thorough picture of the model's performance during validation and training, emphasizing both its strong points and places for development. The model is learning well, but there is still space for development, especially in lowering the variability in validation performance and addressing misclassifications, as shown by the comprehensive metrics, loss curves, and confusion matrix. Figure 13 shows the detection results on a subset of the validation dataset. The images illustrate the model's performance in identifying and classifying different types of tea leaf conditions, including health, dry, TMB, TMB-insect, RSM, mother-leaf, and thrips. The bounding boxes are color-coded for each class, with the confidence scores displayed alongside.



Figure 13. Object Detection Results on Validation Dataset

Each detected object is enclosed within a bounding box, with the predicted class label and confidence score displayed. The confidence score indicates the model's certainty in its prediction. The model shows varying degrees of confidence across different classes. For example, the "health" class has several high-confidence detections (e.g., confidence scores of 0.9 and above), indicating that the model is relatively more certain when identifying healthy leaves. The "Jassid" class also has several high-confidence detections, with scores ranging from 0.3 to 1.0. This variation suggests that while the model can detect Jassid, its certainty varies depending on the image quality and the specific characteristics of the detected region. Some classes, such as "Lopper caterpillar" and "thrips," have fewer detections and lower confidence scores, which might indicate challenges in distinguishing these conditions from others. For instance, the "Lopper caterpillar" class shows a detection with a confidence score of 0.5, suggesting potential room for improvement in the model's ability to accurately identify this class. In several images, the model detects multiple classes within the same image. For example, an image might show detections for both "health" and "mother-leaf," highlighting the model's ability to perform multi-class detection within a single frame.

5. Conclusion

The results provided by the YOLO-V8 model display both the strengths and limitations of the system in detecting and classifying various conditions affecting tea leaves. While the model demonstrates high accuracy in identifying certain conditions, the varying confidence scores across different classes and images reveal areas for improvement. Specifically, the model performs well in certain aspects, but inconsistencies in detection accuracy highlight the need for further refinement to achieve optimal results. Our analysis of the tea plantation reveals a severe infestation by two major pests: the tea leafhopper and the looper caterpillar. Although numerous pest control methods are available, the current environmental and climatic conditions are highly favourable for the pests' life cycles and metamorphosis. As a result, conventional control methods alone are not sufficient to manage the infestation effectively. This underscores the importance of implementing computer vision-based surveillance systems for early detection of pest infestations. By utilizing the YOLO-V8 model for early detection and identification of tea leafhopper and looper caterpillar infestations, we aim to reduce pest-related losses by at least 10%. Early detection enables timely interventions, helping to mitigate damage and improve overall tea yield. The YOLO-V8 model, integrated with computer vision technology, achieved an accuracy of over 97% in identifying these pests, providing a valuable tool for more effective pest management in tea plantations.

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