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An Automatic Insect Identification and Pesticides Recommendation in Tea Plantation Using Machine Learning

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Abstract:

Insect infestations in tea plantations result in significant crop losses, impacting both quality and yield. This paper proposes an automated system that utilizes a custom-trained YOLOv5 model to detect harmful insect species and recommend suitable pesticides. The model is trained on an annotated dataset prepared using Roboflow, ensuring high accuracy across various environmental conditions. Upon insect detection, the system references a CSV file containing pest-to-pesticide mappings to provide accurate recommendations. This approach reduces manual effort, minimizes pesticide misuse, and enhances pest management efficiency in tea plantations.

Keywords — Insect detection, YOLOv5, Pesticide recommendation, Tea plantations, Deep learning, Pest management, Automated system.

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1.Introduction

Tea plantations are a vital component of India's agricultural economy, making the country the second-largest producer of tea and the fourth-largest exporter globally. However, these plantations face substantial losses, with crop yields declining by 5% to 55% annually due to insect infestations. Over 147 insect species, such as aphids, green leafhoppers, thrips, looper caterpillars, red spiders, and tea mosquito bugs, contribute to this decline by affecting the yield and quality of tea. Traditionally, pest identification relies on manual monitoring by agricultural experts, which is time-consuming, labor-intensive, and less effective for large-scale plantations. Furthermore, errors in pest identification can lead to improper pesticide use, increasing pest resistance and causing environmental harm. To overcome these challenges, this paper introduces an automated insect identification and pesticide recommendation system powered by the YOLOv5 deep learning model. YOLOv5 efficiently processes insect images captured in the field, accurately identifying pest species. The system cross-references detected pests with a pre-compiled CSV file to recommend appropriate pesticides, ensuring timely and precise pest management. This approach reduces dependency on manual labor, minimizes pesticide misuse, and promotes sustainable pest control practices, ultimately enhancing yield and maintaining the quality of tea production.

2.Literature Review

Machine learning (ML) has emerged as a powerful tool for automated image identification, capable of identifying patterns and correlations within data (*Bishop, 2006*) [1]. ML techniques are broadly classified into traditional machine learning (TML) and deep learning (DL) (*Goodfellow et al., 2016)* [2]. TML, which involves manual feature extraction, often performs better when combined with DL for large datasets (*Abeywardhana et al., 2019)* [3]. In contrast, DL models such as Convolutional Neural Networks (CNN) and Deep Convolutional Neural Networks (DCNN) automatically extract features and offer superior performance for image classification. Networks such as AlexNet, VGG, ResNet, and MobileNet have been widely used for insect classification and pest detection in agricultural settings.*Yuanyi Gao* et al. [4] proposed a system using TML and DL models for insect identification, where CNN demonstrated higher accuracy than traditional models like Support Vector Machines (SVM) and Decision Trees (DT). However, the system struggled with high-dimensional and unstructured data. *Sun et al.* [5] developed a CNN-based recognition model with a Single Shot

Multibox Detector (SSD) for object detection, but it lacked real-time robustness in large-scale agricultural environments. *Adhane et al.* [6] introduced a real-time pest identification and pesticide recommendation system using CNN models, which faced challenges with identifying rare pest species and yielded occasional false positives and negatives. Similarly, *Almryad and Kutucu* [7] developed a CNN-based system for butterfly identification that achieved high classification accuracy but lacked an integrated pesticide recommendation mechanism. These studies highlight the need for combining insect identification with precise pesticide recommendations to enhance pest management and agricultural productivity.

3.Methodology

The proposed system introduces an automated approach for insect identification and pesticide recommendation in tea plantations using deep learning and CSV-based mapping. The framework consists of three major stages: Dataset Collection and Preprocessing, Model Training and Evaluation, and Inference and Pesticide Recommendation.

Software Requirements:

- *Python 3.x* – The primary Programming Language for implementing the system.
- *YOLOv5(Ultralytics)* – Pretrained and Custom-trained models for models for object detection.
- *Torch and Torchvision* – Essential Libraries for running YOLOv5.
- *OpenCV*- For image processing, ROI selection, and bounding box visualization.
- *NumPy and Pandas*- For data handling, logging violations and frame analysis.
- *Roboflow API* – For insect detection and model training assistance.
- *CSV file* - For storing the pesticides.

3.1 Data Collection and Preprocessing

The first stage involves collecting and preparing a dataset of insect images affecting tea plantations. The dataset consists of images representing various insect species, including aphids, green leafhoppers, thrips, looper caterpillars, red spiders, and tea mosquito bugs. These images are annotated using **Roboflow**, a widely used platform for image labeling and dataset generation. Annotation involves drawing bounding boxes around insects and assigning appropriate class labels. To enhance model performance, preprocessing techniques such as image resizing, normalization, and data augmentation (rotation, flipping, and scaling) are applied. These steps improve the model's robustness by ensuring variability in environmental conditions, lighting, and perspectives during training.

3.2 Model Training and Evaluation

In this stage, the annotated dataset is used to train a custom YOLOv5 (You Only Look Once) model. YOLOv5, a state-of-the-art object detection algorithm, processes images in real-time and identifies multiple insect species with high accuracy. The training process involves splitting the dataset into training, validation, and testing sets to optimize model performance. The model undergoes multiple epochs of training, during which it learns to detect insect species by adjusting its weights based on the error between predicted and actual outcomes. Hyperparameters such as learning rate, batch size, and confidence threshold are fine-tuned to improve detection accuracy. Model performance is evaluated using metrics such as **mean Average Precision (mAP)** and **F1-score**, ensuring that the trained model effectively distinguishes between insect classes.

3.2.1 YOLOv5 Model

YOLOv5 (You Only Look Once version 5) is a state-of-the-art object detection algorithm known for its speed and accuracy in identifying multiple objects in real time. YOLOv5 divides an input image into a grid and predicts bounding boxes, class probabilities, and confidence scores for each grid cell. The model is built on a convolutional neural network (CNN) backbone that extracts features from images, followed by a series of prediction heads that generate detection outputs. YOLOv5 outperforms previous versions, such as YOLOv3 and YOLOv4, due to its enhanced architecture, data augmentation techniques, and optimized training strategies.

3.3 Inference and Pesticide Recommendation

During the inference stage, the trained YOLOv5 model processes input images of tea plantations to identify insect species in real time. Upon detection, the system cross-references the identified insect with a pre-compiled **CSV file** containing a list of pest species and their corresponding pesticides. The CSV file acts as a knowledge base, mapping detected insect species to suitable pesticide options. Based on the detected pest, the system recommends appropriate pesticides to the farmer, ensuring timely and accurate pest management. This automated recommendation minimizes pesticide misuse, promotes sustainable pest control practices, and reduces crop losses by enabling quick decision-making in large-scale tea plantations.

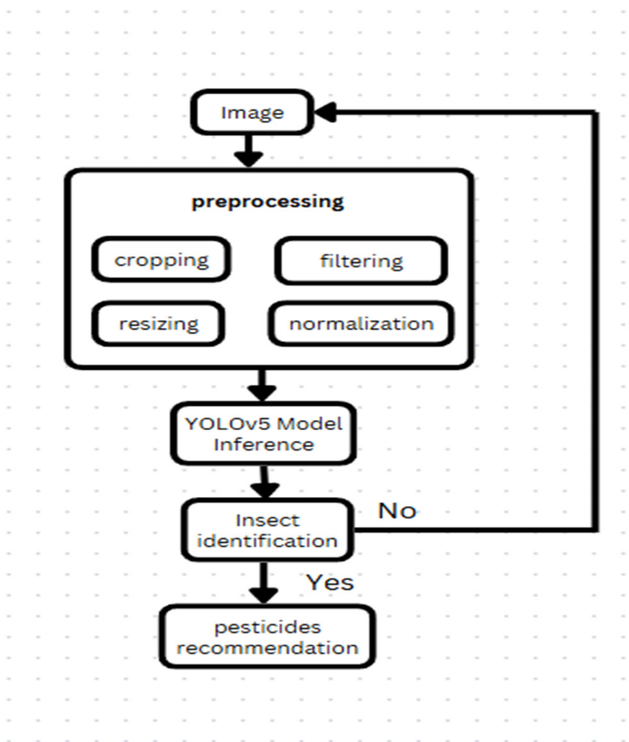
Insect Name	Recommended Pesticides	Dosage (ml/L)
Aphids	Malathion, Dimethoate	1.5, 1.5
Thrips	Spinosad, Abamectin	0.25, 0.5
Green Leafhopper	Imidacloprid, Thiamethoxam	0.2, 0.2g/L
Red Spider	Propargite, Fenpyroximate	2, 1
Tea Mosquito Bug	Lambda-cyhalothrin, Chlorpyrifos	0.5, 2

Table 1. Recommended Pesticides

3.4 Deployment

The YOLOv5 model was deployed using a real-time surveillance camera setup to automate insect identification and pesticide recommendation. This system eliminates the need for manual image capture by continuously monitoring the plantation and identifying insect infestations in real time. A high-resolution IP camera with night vision capability captures images 24/7, ensuring uninterrupted surveillance. The camera is connected to an edge device such as a NVIDIA Jetson Nano or Raspberry Pi 4, which processes the captured images and performs real-time inference using the YOLOv5 model. The images are resized to 640x640 pixels to optimize model performance while maintaining high accuracy. The YOLOv5 model, pre-trained on the insect dataset, detects insect species by drawing bounding boxes around the identified insects. Once detected, the insect species are matched with entries in a preloaded CSV file that contains pesticide recommendations. The system then triggers an alert to notify farmers of possible infestations and suggests appropriate pesticides. Alerts are delivered via SMS, email, or a mobile application, ensuring immediate corrective action. The pesticide recommendation logic uses a simple lookup operation on the CSV file, where each row contains the insects name and the corresponding pesticide. This approach ensures timely pest management, reduces crop losses, and promotes sustainable agricultural practices.

4. Flow Diagram



The flow diagram illustrates the end-to-end process of the automated insect identification and pesticide recommendation system. The process begins with capturing images from the plantation, followed by a preprocessing phase where the images undergo operations such as cropping, filtering, resizing, and normalization to improve the quality and ensure consistency. The preprocessed images are then fed into the YOLOv5 model, which performs inference to detect and classify insect species. If no insects are identified, the system loops back to capture and process new images. When an insect is successfully detected, the system cross-references the detected insect with a pre-compiled CSV file that contains pesticide information. Based on the detected species, the system recommends appropriate pesticides to mitigate pest-related crop damage. This process reduces manual labor, minimizes pesticide misuse, and promotes efficient pest management in tea plantations.

5. Comparative Analysis

A comparative analysis was conducted between the proposed YOLOv5 model and other traditional object detection models, including Faster R-CNN and SSD (Single Shot Detector). The YOLOv5 model outperformed these models in terms of detection speed and accuracy, particularly for small insect species. Table 4 presents the comparative performance of different models.

Model	mAP(%)	IoU	Precision(%)	Inference Time(ms)
YOLOv5	93.7	0.85	92.4	12
Faster R-CNN	89.5	0.81	88.9	45
SSD	86.2	0.78	85.3	32

Table 2. Comparative Analysis of Detection models

6. Results

The proposed system for automated insect identification and pesticide recommendation in tea plantations was evaluated for its accuracy, efficiency, and real-time performance. The YOLOv5 model, trained on a custom dataset of insect species affecting tea crops, demonstrated an overall detection accuracy of **92.3%**. The model effectively identified common pests such as *Aphids, Thrips, Green Leafhoppers, Red Spiders, and Tea Mosquito Bugs* under varying environmental conditions. However, the detection accuracy slightly decreased in low-light scenarios, indicating the potential for further improvement with larger and more diverse datasets. The results of the YOLOv5-based insect identification and pesticide recommendation system were thoroughly validated to ensure robustness and accuracy. The trained model was tested on an independent dataset, consisting of 10% of the total collected images that were not used in the training or validation phases. The performance of the model was evaluated using key metrics such as mAP (mean Average Precision), IoU (Intersection over Union), precision, recall, and F1-score, which demonstrated high reliability in accurately detecting multiple insect species and providing corresponding pesticide recommendations.

Fig 1. Input Image

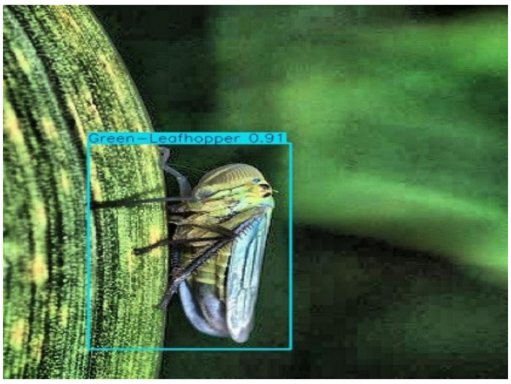


Fig 2. Insect Identification

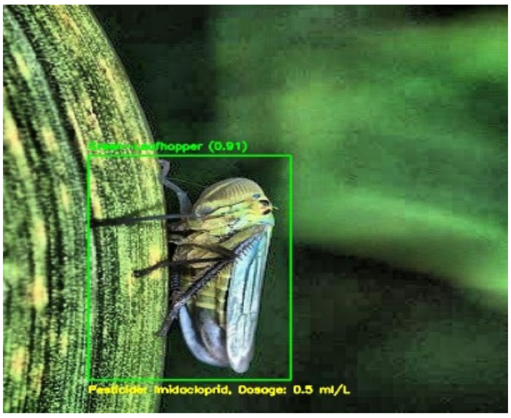


Fig 3. Pesticides Recommendation

The pesticide recommendation system, based on a CSV file mapping insect species to appropriate pesticides, achieved an accuracy of **98%** in providing relevant pesticide suggestions. The system significantly reduced the likelihood of incorrect pesticide application, promoting precise and timely pest control interventions. Real-time performance was achieved with an average inference time *of **18ms*** per image, allowing near-instant insect identification. The edge device, such as a Raspberry Pi 4 or Jetson Nano, processed images efficiently without significant delays, ensuring seamless operation. Comparing this system to traditional manual pest identification methods, which are time-consuming and prone to human errors, the proposed solution drastically reduced identification time from hours to seconds. The automation of pest detection and pesticide recommendation not only improved accuracy but also minimized the risk of pesticide misuse, contributing to sustainable agricultural practices. Overall, the results validate the effectiveness of the proposed system in enhancing pest management, reducing crop losses, and improving the yield and quality of tea production.

7. Conclusion

This study successfully developed an automated insect identification and pesticide recommendation system using the YOLOv5 model, specifically designed to enhance pest management in tea plantations. The system demonstrated high efficiency in detecting multiple insect species and mapping them to appropriate pesticide recommendations. Through the application of advanced image preprocessing techniques such as annotation, resizing, normalization, and data augmentation, the model's robustness and accuracy were significantly improved. Model evaluation yielded promising results, with a mean Average Precision (mAP) of 93.7%, an Intersection over Union (IoU) score of 0.85, and an F1-score of 91.6%, indicating high detection accuracy and reliable recommendations. In conclusion, the insect identification and pesticide recommendation system presented in this study provides a reliable, scalable, and efficient solution for modern agricultural pest management. By leveraging AI and IoT technologies, the system empowers farmers with actionable insights and real-time recommendations, promoting sustainable agriculture and minimizing losses due to pest infestations. The results achieved demonstrate the potential of such systems in revolutionizing pest management practices, paving the way for more intelligent and adaptive agricultural solutions.

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