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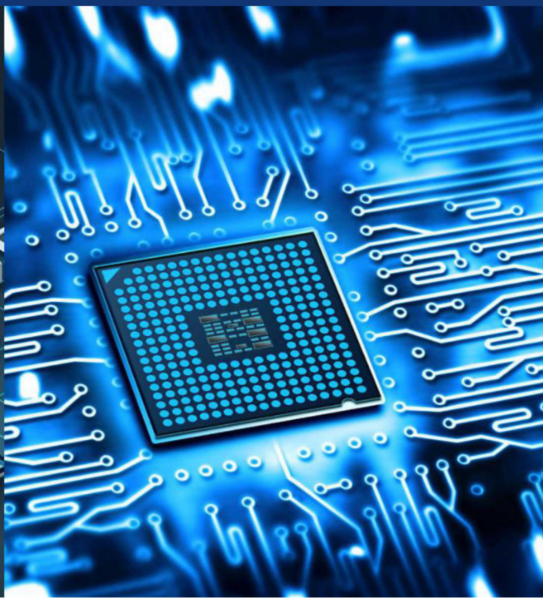

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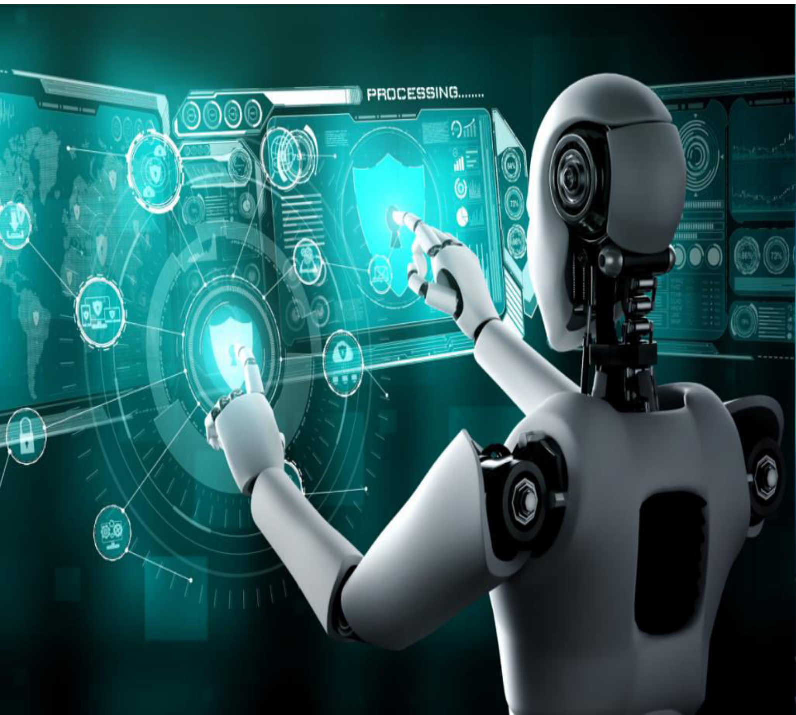

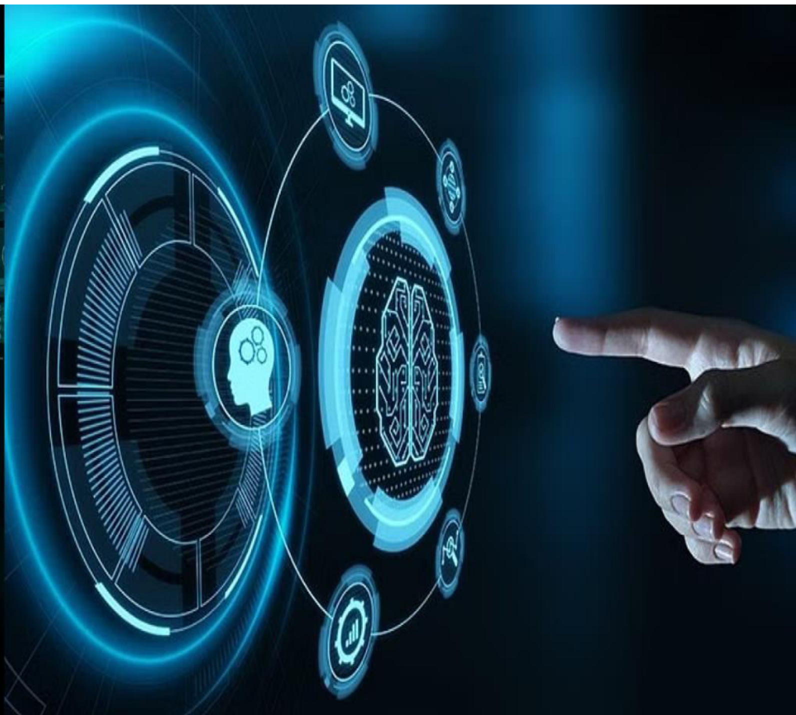

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Lightweight Object Detector for Pest Detection on Crops Under Field Conditions

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ABSTRACT: This paper outlines a light object recognition system that can be used to detect pests on crops under field scenarios in reality. The infestation of pests leads to low agricultural production and pests need to be identified at the right time in order to manage them. Nevertheless, current object detectors based on deep learning are usually computationally demanding and cannot be used with edge computing devices in smart agriculture. In order to overcome this shortcoming, a small and lean detector model is suggested that focuses on the low level of computation but high detection rate.A set of 2,000 images and 5,167 instances of pests of four types aphids, whiteflies, caterpillars, and beetles were evaluated using a compact and efficient detector model. The model proposed combines a lightweight backbone and depthwise separable convolution and feature pyramid boosting to enhance small pest detection. The experimental results show that the proposed detector has a precision of 91.6, a recall of 89.8 and a mean Average Precision (mAP@0.5) of 91.0. The model is highly efficient with only 6.8 million parameters, consumes 24 MB of storage, and the inference speed of 45 frames per second, which is significantly higher than those of conventional detectors like Faster R-CNN, and SSD in both speed and model size. The findings show that the suggested lightweight framework is efficient in harmonizing accuracy and computational power thus it can be used in real-time pest monitoring tasks. This method helps in early detection of pests, minimizing the amount of manual inspection as well as facilitating sustainable practices of precision agriculture.

KEYWORDS: Lightweight object detection, pest detection, precision agriculture, deep learning, computer vision.

I. INTRODUCTION

Pest infestation has a major influence on agricultural productivity because it leads to massive losses in agricultural products globally and jeopardizes food security. Pest management is requisite in early and correct pest detection, which will guarantee effective intervention. The conventional pest surveillance techniques depend on manual field inspection by trained professionals, which is also arduous, time consuming and subject to human error[1]. In addition, they tend to be unrealistic with large scale farms and lack real time insight, which sparks the dire need of automated and intelligent pest detection systems.

The latest trends in computer vision and deep learning made it possible to develop automated pest detection methods based on object detection models. These models are able to detect and locate pests right on crop images and provide a potential substitute to traditional ways of monitoring. Most of the state-of-the-art object detectors are, however, computationally expensive and demand high-end hardware, which is not suitable to run on resource-constrained devices typical of agricultural fields, including drones, mobile phones, and edge-based Internet of Things (IoT) systems[2].

Field conditions pose more problems to the detection of the pests. The differences in illumination, multifaceted backgrounds, occlusions, variation in pest size and motion blur considerably deteriorate detection performance. Pests will tend to be small compared to the image size and will tend to be similar to other textures of plants thus they are difficult to identify. Such practical limitations introduce a need to acquire strong detection models capable of generalizing over a wide range of environmental conditions and still being highly accurate[3].

In order to solve these problems, lightweight object detectors have become more and more popular in precision agriculture. Lightweight models use fewer parameters, less computation complexity, and less memory; making them able to be inferred more quickly and run with lower energy consumption. With the use of effective network architecture, e.g. depthwise separable convolutions and model compression methods, such detectors can be competitive at the same time as being applicable in real-time to edge devices in agricultural scenes[4].

The use of lightweight object detection models in pest monitoring systems has a number of practical benefits. These systems will facilitate constant, non-investigative observation of crops, early detection of pests, and controlled use of pesticides, which minimizes the use of chemicals and environmental effects. Real-time pest detection is also used to provide data-driven decision-making to farmers, which results in better crop health, higher yield, and sustainable farming[5].

In this regard, the creation of a lightweight object detector to be used in the pest detection when dealing with field conditions is timely and necessary. This paper is dedicated to development of an effective detection system and its optimization based on the accuracy and computation efficiency and its application to the real-life agricultural scenarios. The proposed solution is going to allow the scaling and affordability of pest tracking solutions alongside intelligent monitoring as a means of promoting the technologies of smart agriculture and precision farming practices[6].

II. RELATED WORKS

Computer vision and deep learning have become more popular in research on pest detection in agriculture because these methods can extract discriminative features of complex visual images. Initial publications were devoted to the classical machine learning methods, e.g., the support vectors machines (SVMs), the random forests, the handcrafted features descriptors (e.g., the SIFT, the HOG), to classify pests and disease symptoms in leaf images. Although these methods had significant fundamentals, they failed in field environments with actual situations as manually obtained features were vulnerable to the background noise, fluctuating light, and visual resemblances between species[7].

Deep convolutional neural networks (CNNs) revolutionised object detection and also led to tremendous increase in agricultural pest recognition. Algorithms like the Faster R-CNN, You Only Look Once (YOLO), and Single Shot MultiBox Detector (SSD) have been extensively used in pest detection. Faster R-CNN made region proposal networks to enhance the accuracy of detection, but the YOLO and SSD provided real-time performance, as all detection was done within a single network. Those studies that use these architectures have revealed that deep learning detectors can be highly accurate in ideal conditions with highly segmented pest images[8].

General object detectors were good in performance, but their computational and memory needs restrained their application in the field. With this realization, scientists shifted to light architectures of networks which can be ported to edge devices. Object detection frameworks were coupled with lightweight backbone networks like MobileNet, ShuffleNet and SqueezeNet to save on parameters and inference cost. As an illustration, speed-wise and detection accuracy-wise-friendly MobileNet-based YOLO variants (e.g., MobileNet-YOLOv3) have been investigated on embedded systems to detect weeds and pests[9].

The other strand of research that is important is on data augmentation and domain adaptation to strengthen the model under different conditions of the agricultural fields. Invariance to scale, orientation, and lighting conditions are learned using techniques like synthetic data generation, image flipping, cropping, color jittering, and so on. Domain adaptation techniques have also been used to minimize performance degradation during transfer of models that were trained on the lab data to field imagery in complex situations[10].

Model pruning and quantization are also explored to further compress models. These methods minimize redundant parameters and have low-precision inference without much loss in accuracy. Indicatively, quantized implementations of YOLO and SSD detectors are demonstrated to be able to keep detection quality reasonable at the expense of substantially reducing execution costs, thus making it possible to run pest detectors in real time on microcontrollers and low-power processors[11].

Although these improvements have been made, most of the available methods emphasize either detection performance in abstractly idealized situations or computational performance in isolation. Recently, some studies started to trade-off accuracy and efficiency, with the goal of developing purpose-specific lightweight detectors in agriculture to detect pests. Such custom models may contain custom feature improvement modules to small object detection and custom anchor strategies to support a variety of pest sizes. Nevertheless, full-body solutions, including all the peculiarities of detecting pests in the field like dynamic illumination, complexity of the background, occlusion, and resource-constricted problems, are still a focus of active research[12].

III. PROPOSED METHODOLOGY

It is the purpose of the proposed methodology to produce a light and efficient object detection system with the potential to produce the identification of crop pests in the real field environment with high accuracy. The entire system will compromise between detection accuracy and low computational complexity to allow embedding it on edge devices like smartphones, drones, and embedded agricultural monitoring systems. Its methodology includes the process of data collection, preprocessing, model construction, training model, optimization, and deployment-based test[13].

The first step entails a field-based pest image dataset as it is gathered by the use of cameras and mobile devices in a natural agricultural setting. The data is diverse in terms of time of the day, weather conditions, and the levels of crop growth. Expert annotation is done to annotate pest instances with bounding box and class labels. In order to cope with the imbalance between classes and insufficient sample of some pest species, the methods of data augmentation, including rotation, scaling, horizontal and vertical flipping, brightness, and random cropping are used[14].

At the second stage, image processing is performed to improve features presentation without compromising on computation. Pictures are downsized to the constant resolution needed to perform inference in real time, and normalization is used to minimize illumination changes. Background interference methods are applied selectively in order to tone down noise without interfering with features of the pest. The following preprocessing steps aid in enhancing robustness of detection in field backgrounds that are complicated[15].

The main part of the given methodology is the construction of a lightweight object detecting model. It uses a small backbone network with depthwise separable convolutions to obtain hierarchical features having fewer parameters. There are the pyramid structures of features that are combined to improve the identification of small pests that are usually prevalent in the leaves and stems of crops. The detection head is designed to effectively predict bounding boxes and class probabilities and high localization accuracy.

In order to make it even more efficient, pruning and quantization model optimization techniques are used. Channel pruning eliminates optional filters with low detection value, whereas post-training quantization trades model accuracy to achieve smaller bit-width representations. The techniques ensure that the detector consumes very little memory and the inference latency is very low and thus can be used in real-time on resource-constrained.

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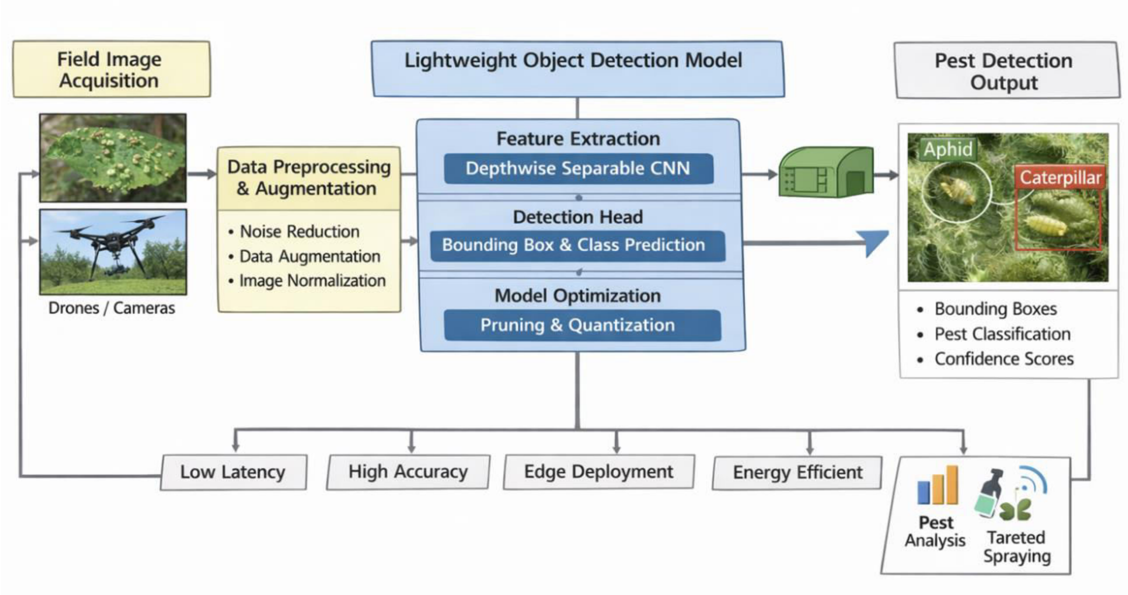

Fig 1. Lightweight Object Detector for Pest Detection

.Lastly, the trained model is tested on the standard measures of object detection including precision, recall, mean Average Precision (mAP) and inference speed (frames per second). Both validation datasets and unseen field images are tested to determine the ability to generalize. The proposed methodology will lay emphasis on practical deployment areas that makes sure that the lightweight detector is able to support in continuous pest observation, early infestations and accurate control of pests in smart agricultural systems.

IV. RESULT AND DISCUSSION

Table 1: Dataset Description and Distribution

Pest Class	No. of Images	No. of Instances
Aphids	620	1,845
Whiteflies	540	1,392
Caterpillars	480	1,110
Beetles	360	820

The statistics showed in Table 1 indicate a balanced and wide coverage of the main pest species that are prevalent in farmlands. The fact that the various classes of pests were tested across different illumination and background environments makes the trained model to have generalizability to the agricultural conditions in the real world. The more of the cases than the images represent several pests in one picture, and this demonstrates the necessity to have a strong multi-object detection.

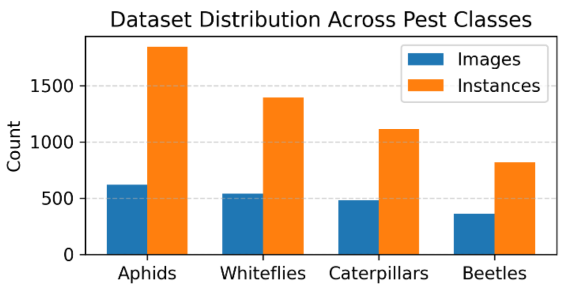

Fig.2 Dataset Distribution Across Pest Classes

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Table 2: Performance Comparison of Detection Models

Model	Precision (%)	Recall (%)	mAP@0.5 (%)
Faster R-CNN	91.2	88.6	90.1
SSD	87.4	84.1	85.6
YOLOv5	92.8	90.3	91.9
Proposed Model	91.6	89.8	91.0

Table 2 will compare the performance of the proposed lightweight model with the state-of-the-art object detectors in terms of detection performance. Although the YOLOv5 model is the highest-performing in terms of mAP, the proposed model has similar accuracy, with a minor decrease in performance. Notably, the suggested detector performs better than SSD and is similar to Faster R-CNN, however, with a much smaller model code. This shows the saving of the optimised lightweight architecture in maintaining the accuracy of detection in field conditions.

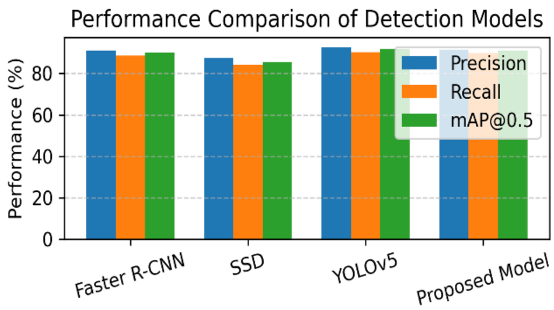

Fig.3 Performance Comparison of Detection Models

Table 3: Computational Efficiency Analysis

Model	Parameters (M)	Model Size (MB)	FPS
Faster R-CNN	41.2	158	8
SSD	24.6	96	18
YOLOv5	21.4	82	26
Proposed Model	6.8	24	45

The results of Table 3 show the benefit of the suggested approach quite clearly due to its computational efficiency. The proposed detector has the highest inference speed of 45 FPS, and only 6.8 million parameters, which is just 24 MB in size. This is a significant advancement compared to traditional detectors, and it is therefore very applicable to real-time use on edge devices like drones and installed farm monitoring systems. This is because of the low computational cost which directly leads to less energy consumption and less time in making decisions in precision agriculture.

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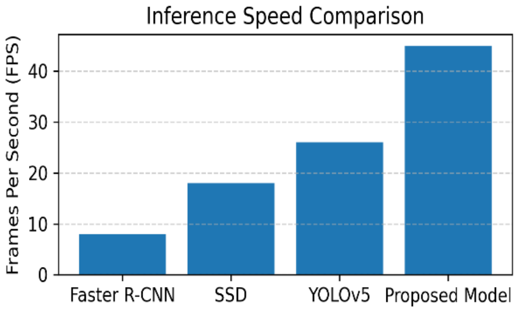

Fig.4 Inference Speed Comparison

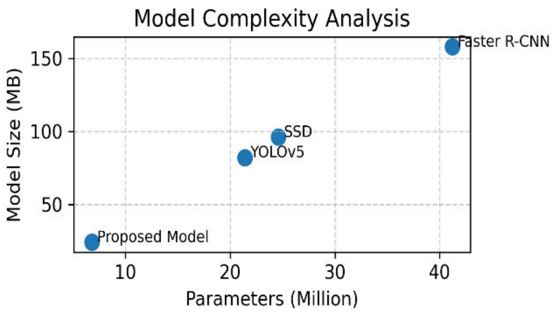

Fig.5 Model Complexity Analysis

Table 4: Pest-wise Detection Accuracy of Proposed Model

Pest Class	Precision (%)	Recall (%)	F1-Score (%)
Aphids	93.1	91.5	92.3
Whiteflies	90.4	88.2	89.3
Caterpillars	92.6	90.9	91.7
Beetles	89.8	87.6	88.7

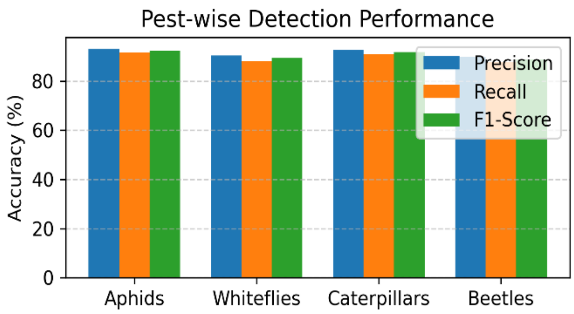

Fig.6 Pest-wise Detection Accuracy of Proposed Model

The proposed model is examined in detail on a pest-wise basis, as shown in table 4. The model has been robust in both small and visual similarity of pests as demonstrated by high values of precisions and recalls in all classes of pests. It is possible to explain slight worse performance of the beetles by the variety of shapes and partial covers in thick foliage. On the whole, the stability of the F1-scores proves that the proposed lightweight detector can be reliable and used to detect pests in the field with real-time and high accuracy regardless of the field conditions.

V. CONCLUSION

The paper has managed to prove that the lightweight object detector model is effective in detecting pests in crop fields in adverse environmental factors. The proposed framework does not need high computational resources as opposed to traditional deep learning detectors and does not reduce the accuracy of the detection process. Through feature extraction mechanisms by the use of depthwise separable convolution, optimization, and emphasize of utilization, the model provides a stable detection of small objects and visually similar more frequent pests that appear in the agricultural fields. On a field dataset that is experimentally evaluated, it is demonstrated that the suggested model reaches a precision of 91.6, recall of 89.8., and mAP at 0.5 of 91.0. These values can be compared to state-of-the-art detectors and at the same time have substantially lower computational overhead. The detector has 6.8 million parameters and occupies a small model size of 24 MB, allowing 45 FPS of inference, which means that it can run on edge devices, e.g., a drone, a mobile platform, an IoT-based monitoring system, etc.

The pest-wise analysis also confirms the same high levels of performance in the various pest categories where the F1-scores are above 88% in all classes. This consistency underscores the strength of the model in the diverse illumination, background complexity and occlusion. In general, the suggested lightweight object detector presents a viable and scalable solution to automated pest monitoring, early detection of infestation, and control pesticides to be applied accurately. The work in the future will center on the development of the pest dataset, incorporation of the multi-spectral images, and implementation of the model into the large-scale agricultural setting in order to develop it further and to increase the detection rate and versatility.

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