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Deep Learning Methods for Detecting Chilli Pests – A Novel Performance Analysis

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ABSTRACT

Ensuring food security is a top goal for all nations, yet infected plants can negatively impact agricultural production and the country's economic resources. In the past, farmers have depended on conventional techniques to enhance crop yield. In recent times, there has been a significant decline in crop production due to pest infestations on Chilli crops. The progress of deep learning techniques facilitates the categorization of diverse sorts of images in practical applications. Especially, detecting multi-class Chilli crop pests with good accuracy using deep learning algorithms is consistently a significant challenge. The proposed study concentrated in identifying pests on Chilli leaves using deep learning methods such as YOLOv5 and YOLOv7. To improve classification accuracy, a new and unique dataset called the standard balanced custom 'Chilli pest dataset' is created with 13,414 pest images. This dataset includes three specific pest classes: Black Thrips, Redmites, and White Fly. We analysed the custom Chilli dataset using YOLOv5 and YOLOv7 to evaluate their effectiveness in detecting pests in Chilli crops and obtained novel detection performance metrics. The resultant parameters mean Average Precision (mAP) for all three pest classes is 98.6% for YOLOv5 and 86.1% for YOLOv7. The YOLOv5s detector demonstrates superior performance compared to the YOLOv7 pest classification, with a 12.5% improvement. The YOLOv7 algorithm achieves its best classification accuracy (86.1%) at a lower epoch (110), while the YOLOv5 algorithm achieves its highest classification accuracy (98.6%) at a higher epoch (350). Nevertheless, despite this distinction, the YOLOv5 algorithm is recommended as the superior detector for accurately identifying pests in well-balanced multi-class pest type datasets, in comparison to YOLOv7, VGG-16 (~92.7%), and VGG-19 (~84.24%) deep learning architectures.

Keywords: image processing, pest detection, convolution neural network, sustainable development, machine learning.

INTRODUCTION

The Second Sustainable Development Goal (SDG-2) 'Zero Hunger' of United Nation (UN) primary objective is to feed 8 billion people in world every day without hunger. But SDG-13 'Climate Action' became a major constraint to achieve SDG by 2030 (Gil et al., 2019). The Indo-Australia and India Large-scale flood events from 1985 to 2016 has shown greater impact on the food production. In addition the past two decades the world is facing either severe drought conditions or cloud burst scenarios results in wetlands to desertification or floods situation (Halgamuge et al., 2017). In most cloud burst cases, there is a big effect on farming, and this effect is bigger on farms and the country's GDP. (Singh et al., 2022). For instance, in Pakistan due to floods in 2022 has affected approximately 33 million people and especially in state of Sindh nearly 4.9 million hectares of agricultural land, almost 57% (2.8 million ha) of the cropland was impacted. The disaster scenario is also similar in India and neighbouring countries. The top five states with the highest reported agricultural losses due to rain and flooding are West Bengal, Madhya Pradesh, Karnataka, Rajasthan, Bihar. Madhya Pradesh witnessed extreme crop destruction on 60.47 lakh hectares in 2019–20 due to heavy floods (Nanditha et al., 2022; Kumar et al., 2020). The major crop loss is happening not only due to floods inundations, but also change in rainfall patterns that is affecting with bacterial, pests, bugs, virus, fungus etc. Many of these illnesses, including *Magnaporthe oryzae* (Germany), *Botrytis cinerea*, *Puccinia* spp., *Fusarium graminearum, Fusarium oxysporum, Black Thrips* (India), *Blumeria graminis*, *Mycosphaerella graminicola, Colletotrichum* spp., *Ustilago maydis*, and *Melampsora lini*, have been identified by researchers and practitioners in recent times (Ceballos et al., 2020; Singh et al., 2023; Chen et al., 2023; Carreón-Anguiano et al., 2020). The states of India such as Telangana, Karnataka, and Andhra Pradesh saw significant crop loss because of the new invasive *thrips* species, *Thrips parvispinus,* particularly the "Black Thrips" on chillies (Lodaya et al., 2022; Sireesha et al., 2021). Due to Thrips attack on Chilli crop, approximate 191.17 m.t crop loss is observed in India during 2021–22 (Figure 1). Especially these sorts of pests and diseases are increasing day-to-day due climate action that implies on nation's economy and leading obstacle parameter for countries GDP. India is an agriculture-based country, where approximate 70% countries people livelihood. It contributes 4% of the world's gross domestic product (GDP) worldwide, and in certain least developed nations, it may represent almost 25% of GDP. In many nations, agriculture plays a vital role in the economy by producing food and raw materials for a variety of businesses (Khan et al., 2020).

There are four main types of leaf diseases in agriculture: fungus diseases, bacterial diseases, viral diseases, and environmental leaf damage. This study is mostly about finding pests that spread these diseases with respect to chilli crop. The primary diseases affecting chilli plants include powdery mildew, leaf spot, leaf blight, viral infections, rust, and root rot. Every illness is caused by specific factors that are influenced by pests and climatic circumstances. In the out of chilli diseases a new disease is *Thrips parvispinus* (Black thrips), Farmers who cultivate chilli peppers are facing a new pest problem that is *Thrips parvispinus* (Black thrips). Typically, pests infest the leaves of the plant, but this new type of pest only attacks the flower buds, causing them to wither and not produce fruit. This pest is not effectively controlled with chemical solutions, but experts are working on innovative agricultural practices. The advent of digital technologies has significantly transformed agricultural practices, particularly in duties linked to pre-harvesting and post-harvesting in the field of agriculture (Mushi et al., 2022; Hatanaka et al., 2022). To a large extent, the pest it is possible that farmers will not be able to see eggs because of their microscopic nature. For most of pests, the egg period lasts for two to three days, the larval period lasts for five days, and the pupae develop inside the galleries. The pupal phase lasts for six days, and the life cycle is finished in thirteen to fourteen days. Beginning in December and continuing through April-May, the pest will have multiple broods. The lifespan of Red-mites ranges from 32 to 60 days, with adults typically living for seven to 10 days. Typically, the farmer will notice pests on a regular basis, usually after a few days (10–15 days), as a result of changes in color of leaves. Today's agriculture is data-driven, precise, and wiser. Advanced IoT systems redesigned 'smart farming'. Innovative farming technologies steadily raise crop yields, reduce irrigation waste, and boost profits. Scaling model learning performance is achieved by Deep Learning (Huo et al., 2024). The portion work is a component of the Smart Agriculture System Using IOT. In the near future, the proposed algorithms will be integrated to benefit farmers. The development of deep learning techniques greatly facilitates the classification of diverse photos in actual scenarios. One of the most critical challenges that are regularly faced by for researchers and practitioners is the detection of multi-class Chilli crop pests with a high degree of accuracy using deep learning algorithms. Identifying pests on Chilli leaves is continually challenging for researchers and practitioners. Jayasuriya et al. (2021) found that deblurring VGG-19 improves its defect detection accuracy to 97.74%. The VGG-16 model detected pest infestations with 99.35% accuracy after being upgraded with the Canny filter. When used with EfficientDet, VGG-19 identified diseases with 99% accuracy. VGG primarily functions as a network for classifying data (Jayasuriya et al., 2021). It has a higher speed and can be trained more quickly. Nevertheless, its detection capabilities are below average compared with You Only Look Once (YOLO) deep learning methods. The YOLO model demonstrated significantly higher accuracy in comparison to the VGG model (Chen, 2024). The inclusion of anchor boxes in the YOLO model potentially expanded the receptive field for feature extraction, which could account for this result. The main aim of this work was to employ YOLO deep learning techniques to improve the precision of detecting chili pests. The v5 and v7 versions of YOLO have been the most successful among all versions (v1 to v9) in terms of achieving higher accuracies in object detection (Jiang et al. 2022; Gillani et al. 2022). A diverse range of pests, including Black Thrips (*Thrips parvispinus*), Red Mites (*Tetrahychus*), and White-fly (*Bemesia Tabaci*), damage the Chilli crop. The research area is plagued by common pests such as Black Thrips, Red Mites, and White-fly, which cause significant damage to the chilli crop. In order to minimize significant agricultural losses, this study focused on conducting experiments using commonly seen pest-infested leaves, including Black Thrips, Red Mites, and White-fly. The current study is centered around two crucial objectives: firstly, to identify pests in Chilli crop and secondly, it examines the relation between epochs and detection accuracy by making learning rate. This research also involves a comprehensive evaluation of YOLO techniques that efficiently identify the Chilli pest. The present study has utilized two classification algorithms, namely YOLOv5s and YOLOv7, to accurately detect pests on chilli plants (Qi et al., 2023; Amara et al., 2023). In order to achieve greater precision, a new dataset for Chilli pests was produced using advanced image pre-processing techniques. The training and validation dataset includes three well-known groups of chilli pests: *Thrips parvispinus*, *Tetrahychus,* and *Bemesia Tabaci* (Horowitz et al., 2020; Santamaria et al., 2020). The YOLOv5 and v7 versions were applied to 13,414 pest photos, and the results achieved more precise detection accuracy. The current work took into consideration these photographs. The current study is limited to only pests data and larvae detection is yet be incorporated.

BACKGROUND

Artificial intelligence-based agricultural disease management systems have emerged as a crucial tool for lowering risk and raising crop yields. The Table 1 provides a detailed overview of prior research in the field of YOLO detector multi-class pest and disease detection on a variety of datasets.

STUDY AREA

The present study area lies under Guntur District (16°18'23.95"N and 80°26'11.54"E), which covers 562 km^2 as shown in location map (Figure 2). The soil and climatic conditions of Guntur District are favourable for Chilli crop growth. Guntur District is a major hub for chilli production, being one of the greatest producers of this crop with 300,000 metric tons each year. Additionally, Guntur city is home to the largest Chilli market in Asia. The Guntur district primarily plants chilli in the Nagarjuna Sagar Right Canal's command area, covering about 120,000 hectares. The Guntur District is famous to produce high-quality red chilli. Along with the high crop production, the study area is highly prone to various pest attacks that result in higher losses during 2020–2022 (Figure 1). Figure 2 displays chilli production in the state of Andhra Pradesh district of Guntur, there was a three-year period from 2020 to 2022. 2020 was a rather steady year for chilli production, with 456,000 metric tons produced. But things changed dramatically in 2021, as the amount of chilli produced fell sharply, reaching 439,035 metric tons—a fall of 16,965 metric tons over the year before. The pattern persisted into 2022, when there was an additional 10,035 metric tons of output decrease, for a total of 429,000 metric tons of chilli produced. There was a progressive decline in chilli production over the chilli production of these three years, which is consistent with the region's dynamic agricultural output. There are several possible reasons for this, including variations in growing techniques, market dynamics, and weather patterns. Other districts, including as Prakasam, Kurnool, Krishna, and Anantapur, are still experiencing it.

CHILLI PEST DATASETS

The dataset comprises 13,414 chilli pest images that are segregated into three classes: Black Thrips (4472), Red Mites (4471), and White-fly (4471). The data is acquired through a high-resolution camera (Nikon D-850 with 45.7 megapixels) from the study area chilli crop fields, and later the data is subjected to image pre-processing techniques to prepare a high-quality dataset. The pre-processing enables the removal of undesirable distortions and enhances specific features that are crucial for the intended use. We employ the following pre-processing techniques in the preparation of the dataset: (i) Data Profiling: The collected raw Chilli dataset underwent profiling phases such as brightness distribution, size distribution, color distribution, and shuffling. To profile Chilli pest datasets, the 'Data Gradients' open-source tool is used that emphasizes

Table 1. Previous works on Pest and disease detection and its accuracy

S. No	Author name	Year	Objective	Technic	Dataset name	No. of classes	Accuracy (mAP@) 0.5
1	Dong et, al.	2024	This work intends to close the gap between current approaches and the developing demands of the agricultural sector, especially regarding crops like rice and maize, by tackling the common issues in pest identification.	MTSPPF, or the Yolo-V5 multi-level spatial pyramid pooling model	IP102 dataset,	9	90.7%
2	Liu et al.	2019	Problem with multiclass pest detection that emphasizes pest localization, which is far more challenging than classification.	Channel-spatial attention (CSA)-PestNet	Multi-class pest dataset 2018	16	75.46%
3	Sun et al.	2024	High-density tiny target pest identification and detection with the goal of resolving the shortcomings of earlier detection systems and manual sorting.	YOLOv5ss	Pest dataset	6	91.0%
4	Dong et al.	2024	It is capable of adaptively choosing the appropriate detection receptive field based on different object sizes.	Scale-aware efficient network (ESA-Net)	LMPD2020. APHIDc.	2	75.3% 68.8%
5	Wang et al.	2024	A prerequisite for successfully managing insect pests is the accurate and quick detection and segmentation of insect pests in crop leaves.	U-Net (DMSAU-Net) model	IP102 dataset	14	92.16%
6	Wei et al.	2024	It is challenging to strike a compromise between real-time detection and counting's quick speed, high accuracy, and lightweight performance.	YOLO_MRC outperforms YOLOv8.	Bactrocera,cucurbitae pest dataset.	1	99.3%
7	Guo et al.	2024	This suggests a two-observation-based open-world pest picture classifier.	NT-Xent loss function and matching network based on ResNet8	A little, open-world pest picture	3	84.29%
8	Sun et al.	2024	We provide a unique lightweight network-based technique for tomato pest and disease diagnosis.	SSNet	Tomato pests	8	98.80%
9	Liu et al.	2020	To perform multi-scale feature detection, this work will construct a dataset of tomato diseases and pests in their actual natural environments and refine the Yolo V3 models feature layer using picture pyramids.	YOLO-V3	1.Early blight 2 Late blights 3 Yellow leaf curl virus 4 Brown spot 5 Coal pollution 6 Gray mold 7 Leaf mold 8 Navel rot 9 Leaf curl disease 10 Mosaic 11 Leaf miner 12 Greenhouse whitefly	12	92.39%
10	Lippi et al.	2021	In precision agriculture (PA) settings, early pest identification is a critical first step in developing crop defense methods.	YOLO-CNN	Pest dataset	2	94.5%
11	Legaspi et al.	2021	This paper's primary goal is to identify and categorize fruit flies and whiteflies for monitoring reasons.	YOLO-V3	Whiteflies and fruit flies	2	83.07%
12	Li et al.	2022	This study introduces YOLO-JD, a deep learning network for image-based jute disease detection.	YOLO-JD	Jute diseases	10	96.63%.
13	Tian et al.	2023	To overcome the difficulties posed by this task, we provide MD-YOLO, a model that can precisely identify three tiny target lepidopteran pests on sticky insect boards.	Multi-scale dense YOLO(MD-YOLO)	Lepidopteran pests	2	86.2%
14	Wen et al.	2022	A large-scale multi-class dense and microscopic pest detection and counting model called Pest-YOLO is proposed.	Pest-YOLO	Pest24	24	69.59%

15	Yang et al.	2023	The suggested approach finds a good balance between detection speed, computing effort, and accuracy to provide quick and accurate pest identification.	Maize-YOLO(YOLO-V7)	Large-scale pest dataset IP102	13	76.3%
16	Chen et al.	2021	Most of the current research concentrates on the laboratory's pest database for analysis, seldom discovering pest illnesses on mobile devices in difficult outside contexts.	YOLO v4	Mealybugs, Coccidae, and Diaspididae	3	97%
17	Guo et al.	2023	Automated surveillance of pest vegetable insects has received little attention in research.	"YOLO for Small Insect Pests" (YOLO-SIP)	Flying vegetable insect pests	2	84.22%
18	Tetila et al.	2024	To assess classification performance, we used a 5-fold cross-validation paired with four measures, and detection performance, we used three metrics.	YOLOv3	Soybean pest	12	0.72
19	Onler et al.	2021	Using the YOLOv5s object detection, our goal was to identify the thistle caterpillar in real time from digital images and videos.	YOLOv5s	Thistle caterpillar	1	59%
20	Chen et al.	2022	Thus, using the YOLOv4 model as a guide, this study used the rice weevil and the red flour beetle as its detecting objects.	YOLOv4	Pest dataset	2	97.55%
21	Huang et al.	2023	We suggest a fresh approach to finding Pomacea canaliculata eggs in rice fields.	YOLO-EP	Eggs of Pomacea dataset	1	88.6%
22	Lyu et al.	2023	The black widow optimization algorithm (BWOA) is employed to optimize the YOLO-SCL model's hyperparameters.	YOLO-SCL	Citrus psyllids	1	97.18%
23	Zhu et al.	2024	The accuracy of the CBF-YOLO network for soybean pest was significantly improved by combining the usage of CSE-ELAN, Bi-PAN, and FFE modules. detection in intricate settings.	CBF-YOLO(YOLOv5s)	Soybean pests	2	81.6%
24	Dai et al.	2023	The suggested approach is more efficient and accurate in identifying pests.	YOLOv5sm	Brown planthopper, rice leaf roller, ladybug, rice ear bug, caterpillar, moth, mirid bug, and corn borer.	10	95.7%
25	Amrani et al.	2023	Our goal was to use an improved artificial intelligence machine learning approach to create a high-performance agricultural insect detector.	YOLO-V3	Pest-24 dataset.	24	72.10
26	Zhang et al.	2022	The enhanced model was applied to the creation of a smartphone-based program for the identification of pests and illnesses in cotton.	YOLOX	Cotton diseases and pests dataset.	5	94.60%
27	Soeb et al.	2023	We introduce YOLO-T, an enhanced YOLOv7 object detection model, for the automatic identification, detection, and resolution of the issue of tea leaf disease detection accuracy in natural scene photos.	YOLOv7 (YOLO-T)	Tea gardens leaf Dataset.	5	96.4%
28	Lippi et al.	2022	Based on pictures of tree branches, we suggest an automated monitoring method to identify gall-mites' infestations online.	You Only Look Once (YOLO)	Hazelnut Dataset.	1	86.7%
29	Agustian et al.	2023	Along with big pests, the model could also identify items that were tiny in relation to the scale of the image.	YOLOv5ss	IP-23 dataset	4	81.3%
30	Zhu et al.	2023	Therefore, the purpose of this research is to provide a novel approach for employing polygons to identify areas infested by pests.	Poly-YOLOv8	PolyCorn dataset.	1	67.26%

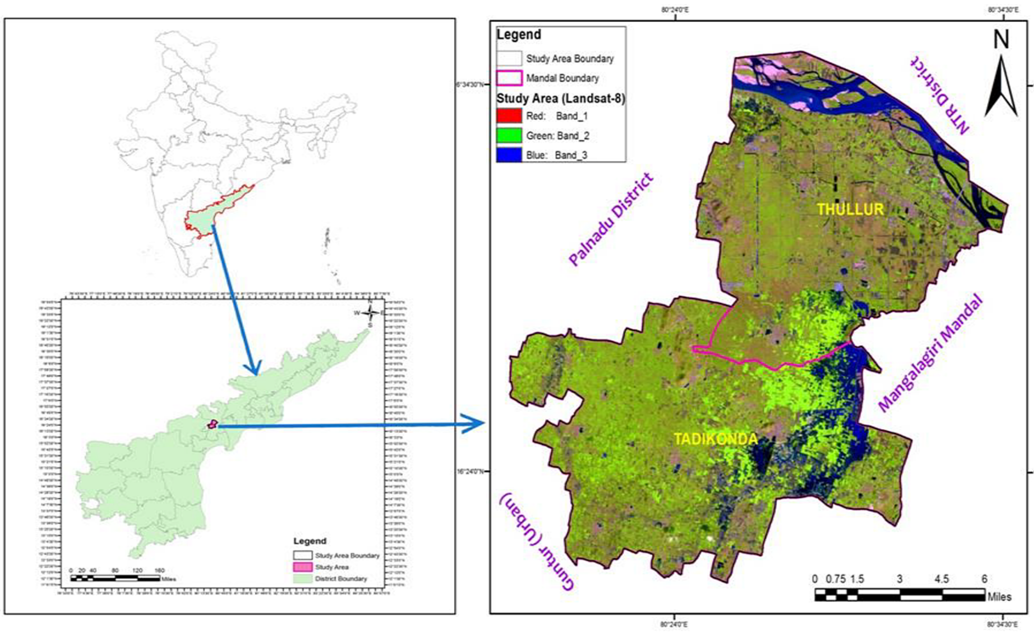


Figure 1. Study area location map (NASA Earth Explorer (Landsat-8))

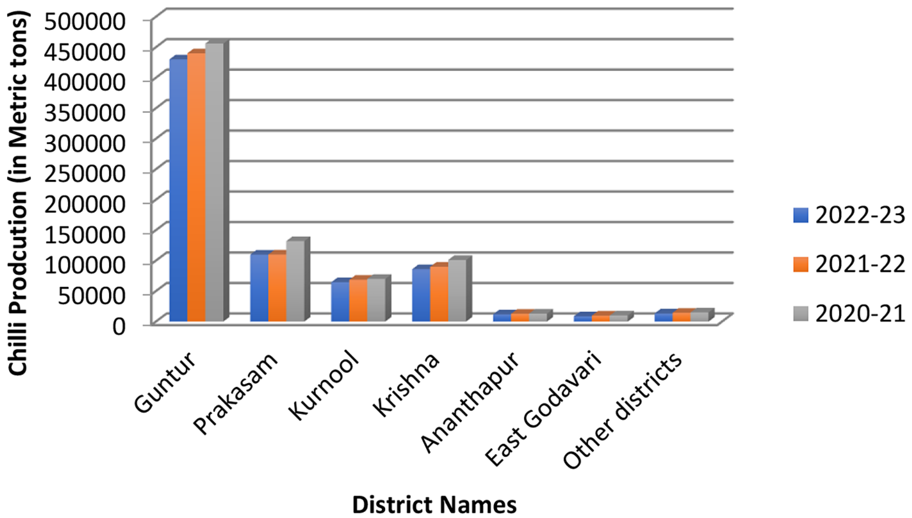


Figure 2. Chilli produced across Andhra Pradesh in Financial years 2020–2022 by all states (fao.org/faostat/en/)

image quality parameters such as convexity, fine details, segments, brightness and color distribution, aspect ratios, and resolution of pest images (Towfek et al., 2023; Blanchy et al., 2020). (ii) Data Cleaning: We removed incorrect, corrupted, incorrectly formatted, redundant, or incomplete images of chilli pests from the dataset. It was 559 photos of Black Thrips that were obtained, and 32 photographs were eliminated from the collection. Similarly, I took 558 photographs of red mites and deleted 24 of them; the majority of them are duplicates, and only a few of them are blurry. Similar to the previous example, I collect 558 white-fly photos and eliminate 14 of them due to their low resolution and brightness. We eliminate 70 outliers from the real dataset of 1675, and consider the remaining 1605 photos to restore the dataset's equilibrium. (Dhiman et al., 2023). (iii) Balanced Dataset: The accuracy of classifying balanced datasets is considerably greater and less biased when compared to imbalanced datasets. A total of 1675 high-resolution images of pests were carefully chosen and downsized to a resolution of 640×640 pixels for the current research in each category. These images are thereafter subjected to augmentation (Alsubaei et al., 2024). (iv) Augmentation: An eight-fold augmentation procedure is applied to each pest class image and escalated to 4471 by rotation, blurring, noising, and flipping at different angles (Ameen et al., 2023). We divide the dataset into three categories, setting aside 20% for validation, 10% for testing, and 70% for training. The present dataset comprises three pest-affected wide variety of chilli leaf datasets, like 26–26, 275 – varieties for (Black Thrips), 273–273, 274, 341, 350 – varieties for (Red Mites), Kalyani, and 555 – varieties for (White-fly).

Black thrips (*Thrips parvispinus*)

The *Thrips parvispinus* insects are special type of insects that damages chilli crops at larger volume in less span of time. All around the planet, but particularly in tropical and temperate regions, are these insects. From the time of seeding until the final harvest, these caterpillars consume the pith and sap. These insects consume a variety of horticultural crop, decorative plants, and vegetable crops. This insect severely lowers the harvest and is greatly anticipated in all our state's chilli farming regions according to Figure 3.

Red mites (*Tetrahychus*)

The Red mites or Spider mites or *Tetrahychus* are one of the popular pests for Chili crop in the study area. The Red mite causes severe damage to the Chili crop leaves become infected and exhibit crinkling and downward curling. In addition, buds undergo desiccation and subsequently detach. In the initial phase, the presence of pests causes a decrease in plant growth and the ability to produce flowers, resulting in a halt in fruit development. The dataset comprises of 4,471 Red Mites images as shown sample images in Figure 4.

White-fly (*Bemesia Tabaci*)

Another significant insect that harms chilli crops is the *Bemesia Tabaci*. When their baby worms come out of the grids, they walk a little distance on the leaves in search of a good location to suck the juice, settle there, and do just that. Aside from that, the honey-like substance excreted by these insects harbors black mold, which impedes photosynthesis. The result is that the plants get weakened and stunted. In addition, whiteflies serve as messengers for the Gemini virus, which causes leaf blight. The dataset consists of 4,471 photos of White-fly, as depicted in the sample photographs presented in Figure 5.

DEEP LEARNING ARCHITECTURE

You only look once – 5 (YOLOv5) detector

Model for computer vision YOLO family includes YOLOv5s. YOLOv5s is employed in object recognition. There are four main versions of YOLOv5s, each with a different accuracy level: small (s), medium (m), large (l), and extra-large (x). Object detection, which extracts characteristics from pictures, is the primary application of YOLOv5s. These traits are predicted to define object boundaries and classes. Three components make up the YOLOv5s model:

- Backbone (CSP-Darknet-53): A multiscale convolutional neural network.
- Neck (PANet): A series of layers that fuse and refine visual features before prediction.
- Head (YOLO-Layer): Uses neck characteristics to forecast box and class (Figure 6).

Figure 3. Sample dataset of black thrips images

Figure 4. Sample dataset of red mites' images

Figure 5. Sample dataset of white-fly images

Backbone: CSP-DarkNet-53 training architecture

DarkNet-53 is enhanced by CSP-Darknet-53 using a novel technique known as Cross Stage Partial Network. (CSPNet). The divide and conquer strategy used by CSP-DarkNet-53 allows the system to divide the input data into smaller sections that are easier to process. It then uses cross-stage connections to combine these sections back into a larger representation of the input data. Typically, the CSP-DarkNet-53 training architecture splits the given input image data into two convolution layers (1×1). The part – 1 has only one convolution layer and whereas part – 2 contains four convolution layers, out of which 3 convolutions is of 1×1 filter sizes and other one is of 3×3 filter size. Lastly the two parts are merged

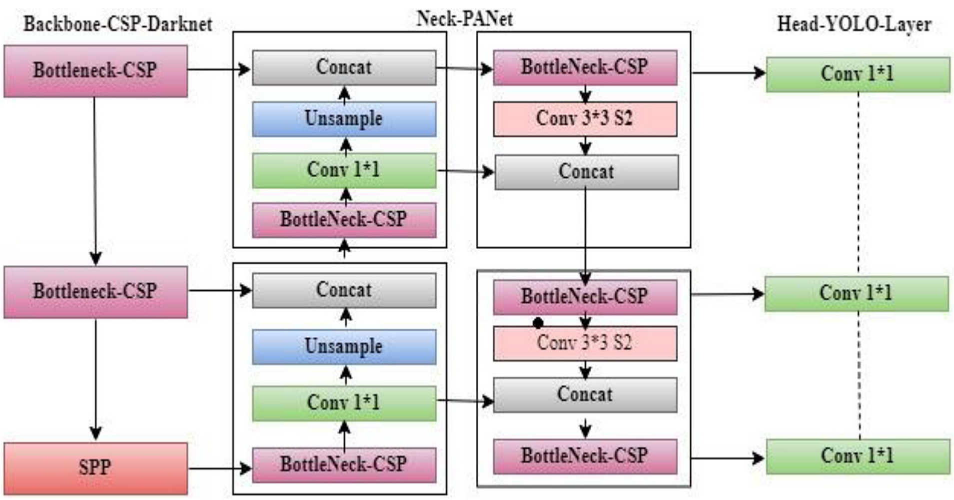


Figure 6. Yolov5 architecture with CSP-DarkNet(Backbone), PANet(Neck) and yolo layer (head)

to one additional convolution layer of size 1×1 and output features are classified (Figure 7).

Neck: PANet training architecture

The PANet (Path Aggregation Network) comprises three different training phases for improving performance. A bottom-up path is augmented to make low-layer information easier to propagate. We design adaptive feature pooling to allow each proposal to access information from all levels for prediction. Bottom-up Path Augmentation: This technique produces less than 10 layers across these levels. The CNN trunk in FPN has a long route through 100 + layers from low to high. Augmented Bottom-up Structure: The progression from P2 to P5 spatial size is down-sampled by factor 2. We utilize {N2, N3, N4, N5} to represent newly created feature maps for {P2, P3, P4, P5}. Adaptive Feature Pooling: It assigns minor suggestions to lower feature levels and large ones to higher ones. Although easy and effective, it may yield suboptimal outcomes. Fully-connected Fusion: Fully-connected layers (fc layers) have distinct qualities compared to FCN, which predicts each pixel using a local receptive field and shares parameters across different geographical locations. In contrast, fc layers are location-sensitive as they use different parameters to forecast different spatial locations. This allows them to adapt to varied spatial settings as shown in Figure 8.

You only look once -7 (YOLOv7) detector

The most recent model in the YOLO model series is the v7 model. Object detectors in the YOLO paradigm only function in one step. A backbone is used in YOLO model image frame processing to extract features. Before the characteristics are sent to the head of the network, they are combined and integrated in the neck. Bounding box outline placements and categories for objects are predicted by YOLO. To calculate its final forecast, YOLO uses non-maximum suppression (NMS) during post-processing. The authors of YOLOv7 build on earlier research about the distance a gradient must travel to back-propagate between layers and the usage of memory for layer storage. Their

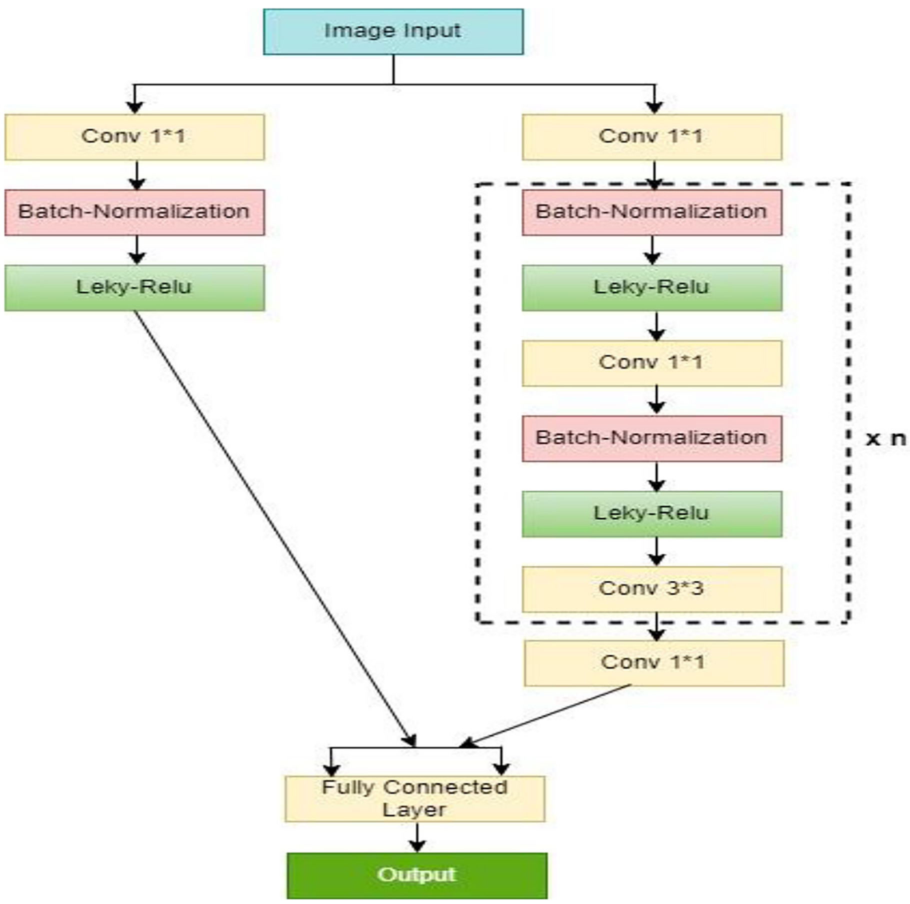


Figure 7. Backbone training architecture of CSP-DarkNet-53

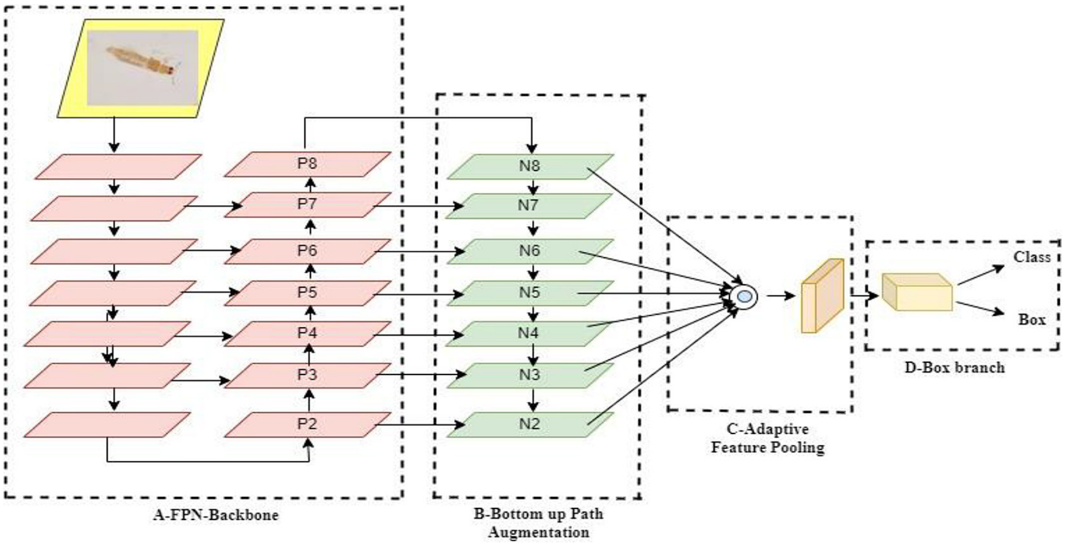


Figure 8. Neck training architecture of PANet of pest classes

network will be better able to learn if the gradient is shorter. As the last layer aggregation, they used Extended Efficient Layer Aggregation (E-ELAN), which is an expanded variant of the ELAN computational block (Figure 9) and YOLOv7 architecture for pest class is defined in Figure 10.

MATHEMATICAL NOTATIONS

This section discus the mathematical notations related to the classification performance metrics such as Training and validation. In general, the training and validation parameters are further classified into coordinate (Box), Objectness and Classification accuracy. The Coordinate loss occurs due to a box prediction not exactly covering an object. The Objectness loss due to a wrong box-object IoU prediction. Lastly the Classification loss express the deviations from predicting '1' for the correct classes and '0' for all the other classes for the object in that box. The loss function is computed in Equation 1.

$$Loss = \lambda_{cd} \sum_{i=0}^{S^2} \sum_{j=0}^{B} 1_{ij}^{obj} [(x_i - x_i')^2 + (y_i - y_i')^2] + \lambda_{cd} \sum_{i=0}^{S^2} \sum_{j=0}^{B} 1_{ij}^{obj} \left[\left(\sqrt{w_i} - \sqrt{w'_i}\right)^2 + \left(\sqrt{h_i} - \sqrt{h_i'}\right)^2\right] + \sum_{i=0}^{S^2} \sum_{j=0}^{B} 1_{ij}^{obj} (C_i - C_i')^2 + \sum_{i=0}^{S^2} \sum_{j=0}^{B} 1_{ij}^{noobj} (C_i - C_i')^2 + \sum_{i=0}^{S^2} 1_{ij}^{noobj} \sum_{c \epsilon class} \left(p_i(c) - p_i'(c)\right)^2 \quad (1)$$

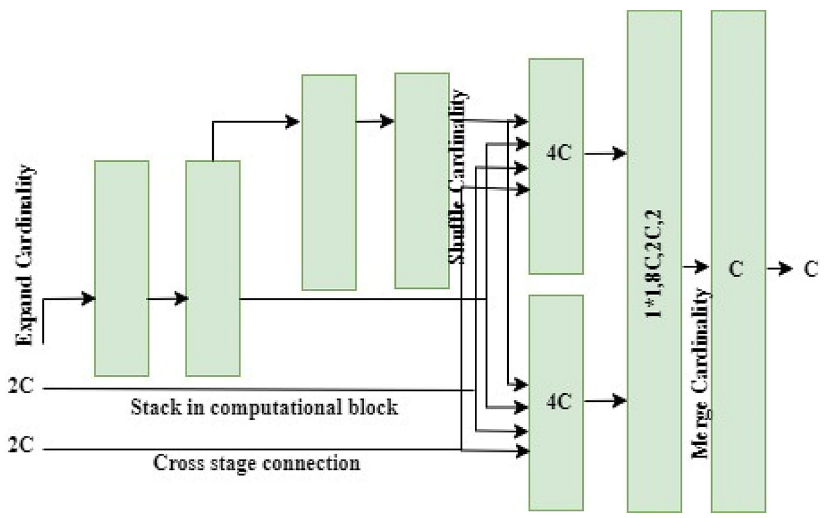


Figure 9. YOLOv7 (E-ELAN) backbone architecture

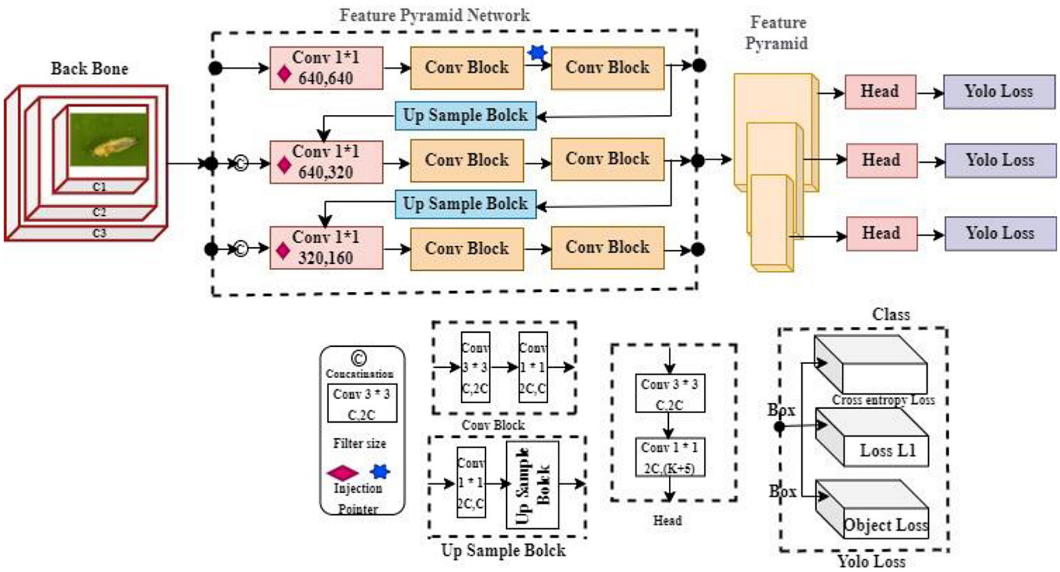


Figure 10. Layered architecture of Yolo v7 architecture for pest class

The coordinate function for optimal box detection is represented by 'cd', while the 'objectness loss function is referred to as 'obj' in the YOLO-V1 loss function. YOLO V2 and V3 implemented a residual scale prediction instead of direct width and height forecasts to ensure that the loss function is based on relative scale error rather than absolute scale error. The mean Accuracy Precision (mAP) is articulated as average accuracy precision classification as in Equation 2, where 'AP' refers the average precision.

$$mAP = \frac{1}{N}\sum_{i=1}^{N} AP_i \qquad (2)$$

RESULTS AND DISCUSSION

Pest detection using Yolo-5

Classification performance metrics

In general, the performance analysis of object detection from a multi-class image dataset is computed based on five metrics namely, coordinate Loss, objectness, classification, precision, and recall.

Training loss

a) Box validation – the box loss indicates how successfully the model locates an pest object's centre and the pest class object is covered by the predicted bounding box and achieved 0.033569 classification training accuracy.
b) Objectness – the likelihood that an object will be present in a Region-of-Interest (RoI) of interest is measured by objectness loss. The objectness training loss on pest dataset is 0.016341, which is very minimal and treated as good fit that there is an object in the image window.
c) Classification – classification loss is a measure of how well the algorithm can predict a pest object on leaf class. The loss function for training classification value is 0.007425, which is very low value and obtained good classification accuracy. The Precision value is 0.860379 that shows the predict model is correct in predicting the target Pests class. The Recall value is 0.804229 that represents that the Yolo5 model resulted well in finding all objects of the targeted pests' class. The mean Average Precision (mAP) is 0.849624 that represents very good classification.

Validation loss

A statistic called validation loss is used to evaluate how well a deep learning model performs on the validation set. A section of the dataset designated specifically for validating the model's performance is called the validation set. Calculated using the total of the mistakes for every example in the validation set, the validation loss is like the training loss. Figure 12 and 13 describes the pest class confusion matrix and YOLOv5s Chilli Pest Classification peak performance metrics at 350 epochs. The results screenshot of YOLOv5 detected pest is shown in Figure 14 and pest classification peak performance for YOLOv5 is represented using PR curve and F1-score in Figure 15.

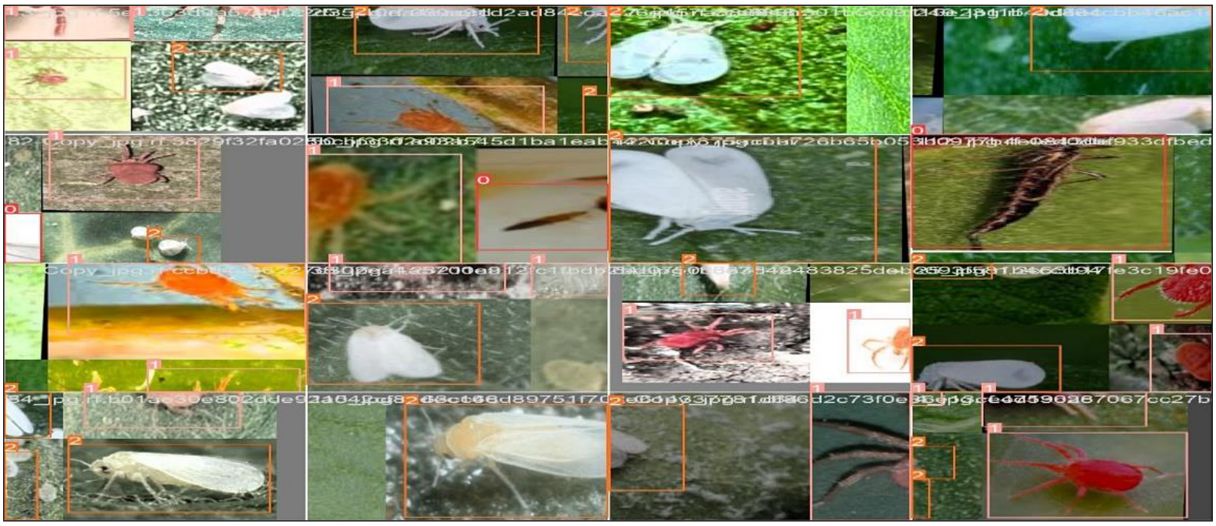


Figure 11. Labelling of various chilli pest class during Training phase (PANET)

a) Box validation – the box loss measures how well the model finds the center of a pest item, if the pest class object is covered by the projected bounding box, and whether the classification training accuracy was 0.033569 (Figure 13).

b) Objectness – the likelihood that an object will be present in a Region-of-Interest (RoI) of interest is measured by objectness loss. The objectness training loss on pest dataset is 0.016341, which is very minimal and treated as good fit that there is an object in the image window (Figure 13).

c) Classification – classification loss is a measure of how well the algorithm can predict a pest object on leaf class. The loss function for training classification value is 0.007425, which is very low value and obtained good classification accuracy. The Precision value is 0.860379 that shows the predict model is correct in predicting the target Pests class. The Recall value is 0.804229 that represents that the Yolo5 model resulted well in finding all objects of the targeted pests' class. The mean Average Precision (mAP) is 98.6% that represents very good classification (Figure 15).

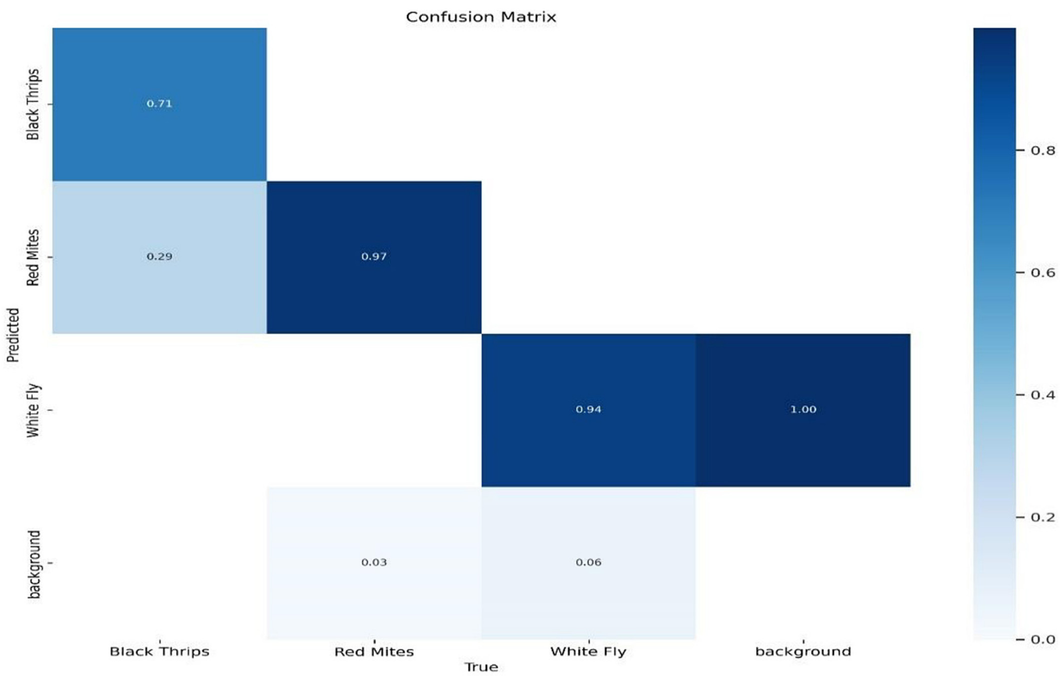


Figure 12. Confusion matrix of chilli pest classification using Yolo5

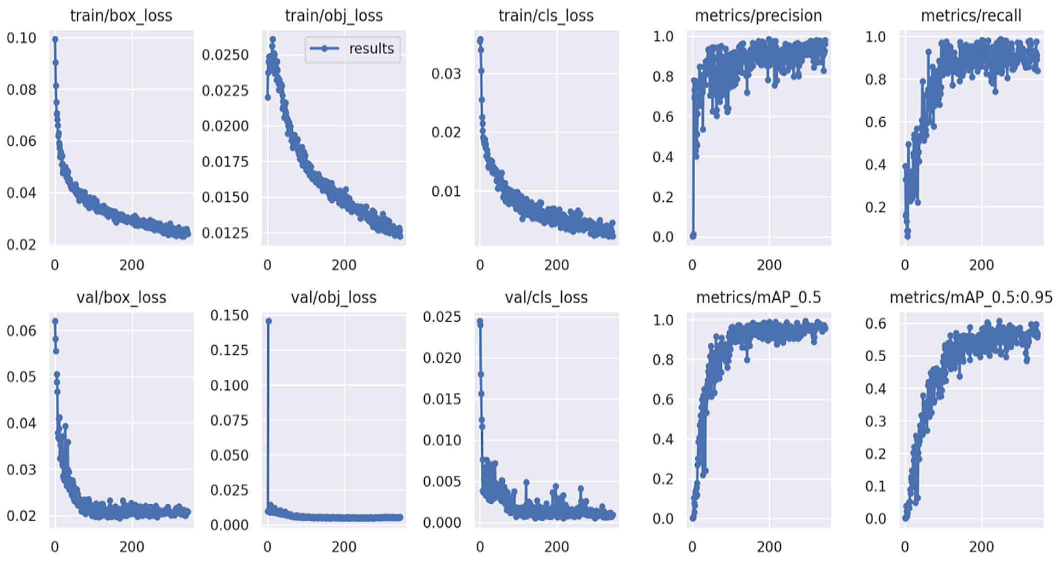


Figure 13. YOLOv5s Chilli Pest Classification peak performance metrics at 350 epochs

Figure 14. Results of multi-class chilli pest detection represented with bounding boxes using YOLOv5s on custom chilli pest dataset (red mites, white fly and black thrips)

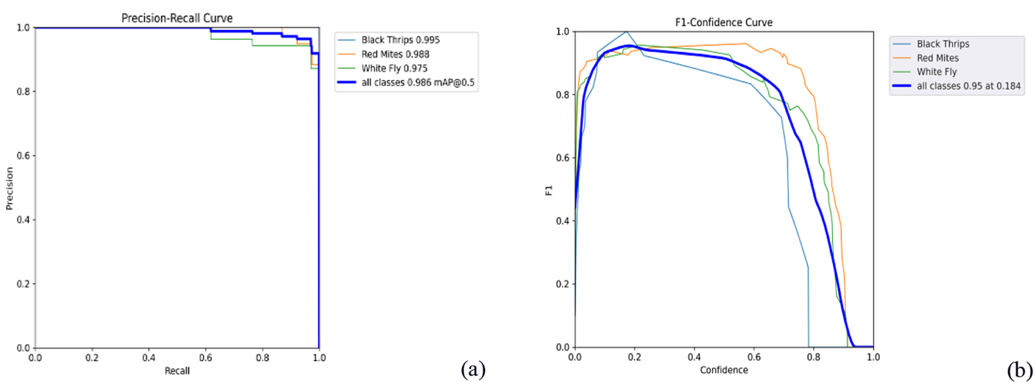


Figure 15. (a) YOLOv5s chilli pest classification peak performance metrics P-R curve. (b). F1-confidence score at 350 epochs

Pest detection using Yolo-7

Classification performance metrics

In general, the performance analysis of object detection from a multi-class image dataset is computed based on five metrics namely; coordinate Loss, object-ness, classification, precision, and recall. Figure 16 shows the Labelling of various Chilli pest class during Training phase. The results screenshot of YOLOv7 detected pest is shown in Figure 19 and pest classification peak performance for YOLOv7 is represented using PR curve and F1-score in Figure 20. Figure 17 and 18 describes the pest class confusion matrix and YOLOv7s Chilli Pest Classification peak performance metrics at 110 epochs.

Training loss

a) Box validation – the box loss shows how well the model locates the center of a pest item, the extent to which the pest class object is covered by the predicted bounding box, and the classification training accuracy of 0.033569.
b) Object-ness – the likelihood that an object will be present in a Region-of-Interest (RoI) of interest is measured by object-ness loss. The objectness training loss on pest dataset is 0.016341, which is very minimal and treated as good fit that there is an object in the image window.
c) Classification – classification loss is a measure of how well the algorithm can predict a pest object on leaf class. The loss function for training

Figure 16. Labelling of various chilli pest class during training phase (PANET)

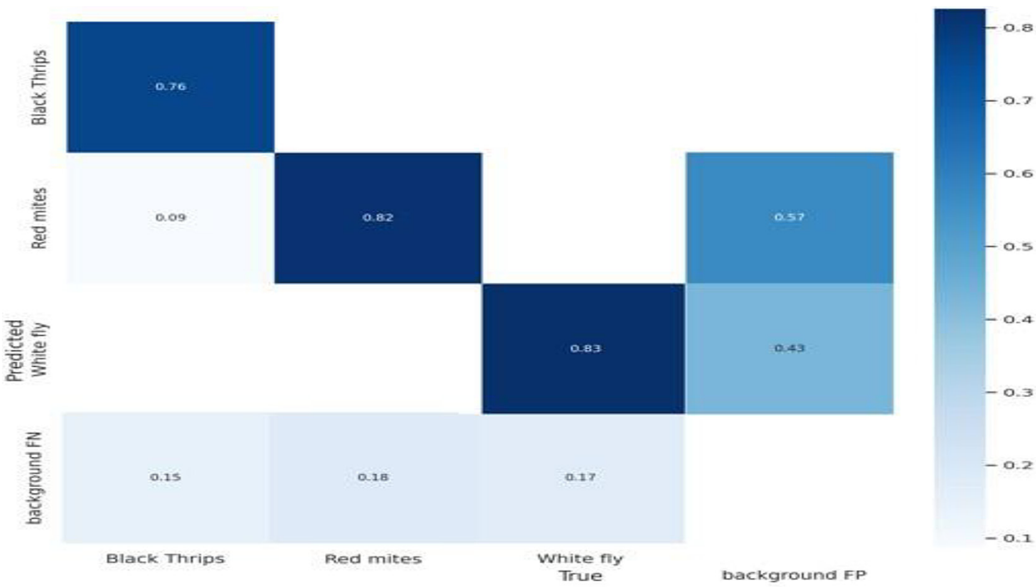


Figure 17. Confusion matrix of Chilli Pest Classification using YOLOv7

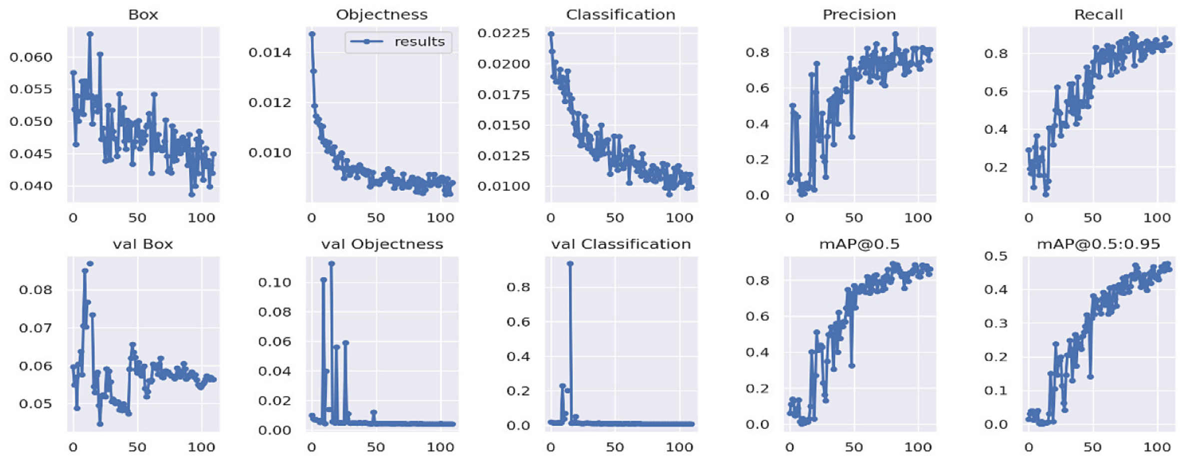


Figure 18. YOLOv7 chilli pest classification peak performance metrics at 110 epochs

classification value is 0.007425, which is very low value and obtained good classification accuracy. The Precision value is 0.860379 that shows the predict model is correct in predicting the target Pests class. The Recall value is 0.804229 that represents that the Yolo5 model resulted well in finding all objects of the targeted pests' class. The mean Average Precision (mAP) is 0.849624 that represents very good classification.

Validation loss

A deep learning model's performance on the validation set is evaluated using a statistic called validation loss. A subset of the dataset designated specifically to verify the model's performance is known as the validation set. Constructed from the total of the errors for every example in the validation set, the validation loss is computed similarly to the training loss.

a) Box validation – the box loss measures how well the model finds the center of a pest item, if the pest class object is covered by the projected bounding box, and whether the classification training accuracy was 0.033569 (Fig. 18).
b) Object-ness – the likelihood that an object will be present in a Region-of-Interest (RoI) of interest is measured by object-ness loss. The object-ness training loss on pest dataset is 0.016341, which is very minimal and treated as good fit that there is an object in the image

Figure 19. Results of Multi-class Chilli pest detection represented with bounding boxes using YOLOv7 on custom chilli pest dataset (red mites, white fly and black thrips)

window (Figure 18).

c) Classification – classification loss is a measure of how well the algorithm can predict a pest object on leaf class. The loss function for training classification value is 0.007425, which is very low value and obtained good classification accuracy. The Precision value is 0.860379 that shows the predict model is correct in predicting the target Pests class. The Recall value is 0.804229 that represents that the Yolo5 model resulted well in finding all objects of the targeted pests' class. The mean Average Precision (mAP) is 86.1% that represents very good classification (Figure 20).

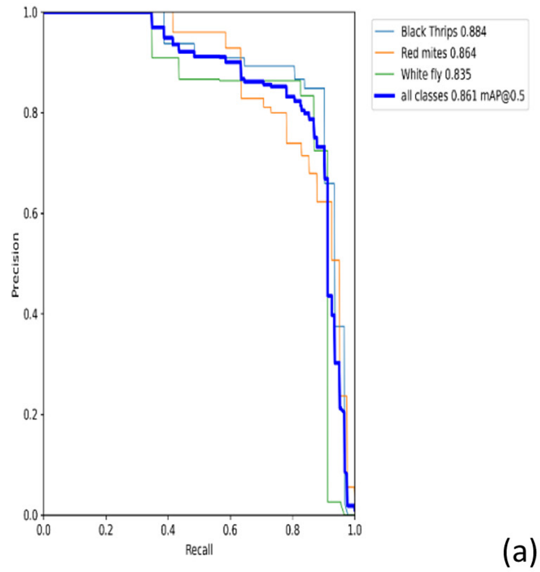
Influence of classification parameters

Impact of epochs

The change in epochs has shown a greater impact on Precision, Recall, F1-Score and P-R curve as shown in the Figure 21 and 22. The YOLOv5s and v7 algorithm is executed by varying 25 epochs to 350 epochs and computed accuracy for every 25 epochs. The peak classification accuracy of the pest dataset achieved at 310 epochs in YOLOv5s and 110 epochs in YOLOv7 as represented in Table 2 and 3. From the Figure 21 it is also observed that lower epochs resulted lower accuracy for Yolo5, whereas the moderate epochs in between 100 to 250 results higher accuracy for Yolov7. And from Figure 22 it is observed that always Recall values are higher than Precision value and followed by PR and F1 Score.

Precision

For precision, Table 2 shows that YOLOv5s outperforms YOLOv7 in all circumstances. YOLOv5s had 61%, 86% and 87.1% for Black Thrips, Red mites, and Whitefly, while YOLOv7 had 51%, 41% and 52%. In overall class detection, YOLOv5s



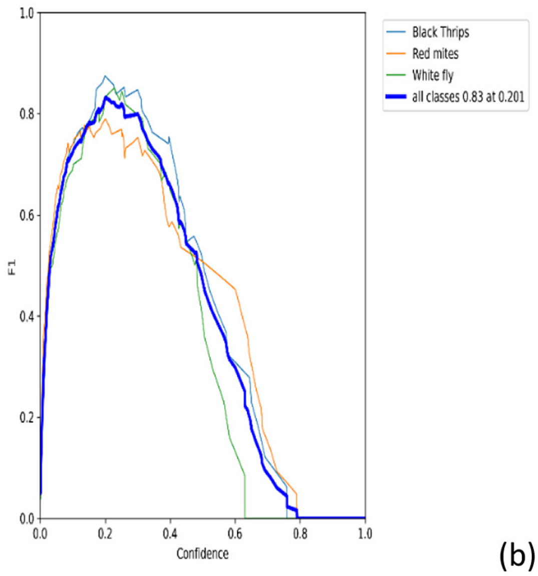


Figure 20. YOLOv7 chilli pest classification performance metrics (a) P-R curve and (b) F1-confidence score

Table 2. Training and validation results of YOLOv5s and YOLOv7

S. No.	Features		YOLO V5	YOLO V7
1	@mPA_0.5		98.6	86.1
2	Epoch		350	110
3	Training	Box loss	0.033569	0.047857727
4		Objectness loss	0.016341	0.009315773
5		Classification loss	0.007425	0.013113764
6	Validation	Box loss	0.860379	0.630452273
7		Objectness loss	0.804229	0.587972706
8		Classification loss	0.849624	0.285897575

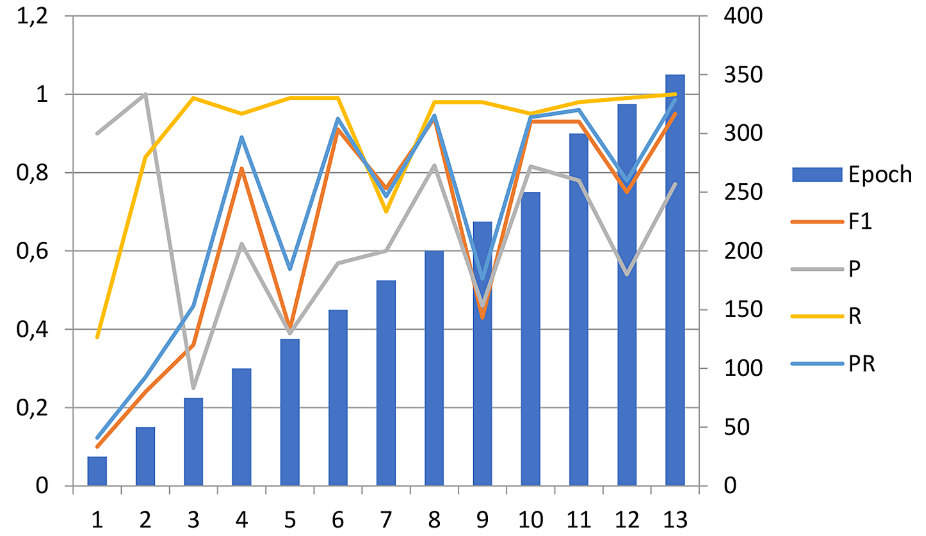


Figure 21. Performance analysis YOLOv5s of F1-Score, precision, recall, precision-recall with respect to epochs

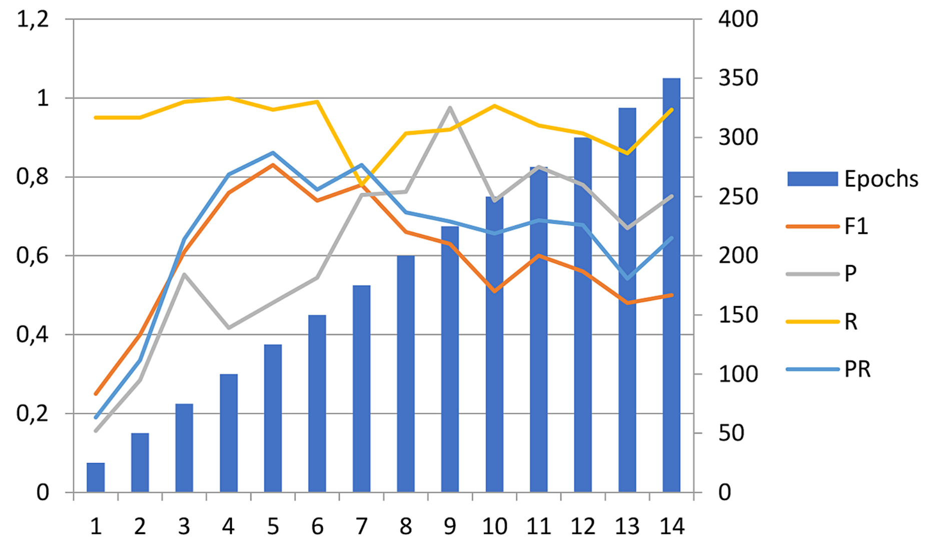


Figure 22. Performance analysis YOLOv7 of F1-Score, precision, recall, precision-recall with respect to epochs

has 12.5% more true positives than YOLOv7. Both models detect more Black Thrips than other classes, 4% more than YOLOv7. This model will efficiently identify Black Thrips more than other classes.

Recall

Table 2 shows that YOLOv5s outperforms YOLOv7 in Black Thrips, Red mites, and Whitefly, pest detection. YOLOv7 surpasses YOLOv5s in class recall, red mites, and Whitefly, with 98.5%, 99%, 98.5% vs. 98%, 98%, and 94%. The difference between three pest classes difference between YOLOv5s and YOLOv7 is 1.1%, 0.1% and 0.45% respectively during detection. YOLOv7 outperformed YOLOv5s in identifying the red mites and Whitefly classes, improving class recall by 3%. Compared to YOLOv7, YOLOv5s has better Black Thrips class detection recall.

F1-confidence score

The best F1 score, 0.86, with a confidence threshold of 0.523, is displayed by the F1 confidence curve. YOLOv5s pest detection outcomes using a 0.523 confidence threshold. At a confidence threshold of 0.523, the F1 confidence curve shows the highest F1 score of 0.86. YoloV7 has a 0.523 confidence threshold for pest detection.

Precision about mAP@0.5 and mAP@0.5:0.95

When comparing the findings in Table 2, it can be observed that YOLOv5s consistently

Table 3. Detection performance analysis of Chilli pest detection between YOLO-v5s and YOLOv7

No.	Features		Detection accuracy						Difference YOLO (V5s–V7)		
1	Model		YOLO V5s			YOLO V7					
2	Class name		Black thrips	Red mites	White fly	Black thrips	Red mites	White fly	Black thrips	Red mites	White fly
3	Metrics	Precision	0.610	0.860	0.871	0.51	0.41	0.52	0.1	0.45	0.351
4		Recall	0.985	0.99	0.985	0.98	0.98	0.94	0.111	0.01	0.045
5		Accuracy precision	0.995	0.988	0.975	0.884	0.864	0.835	0.111	0.124	0.14
6		mAP_0.5	0.986			0.861			0.125		
7		mAP_0.5:0.95	0.66			0.39			0.27		

outperformed YOLOv7 in terms of accuracy, with overall class results in mAP@0.5 and mAP@0.5:0.95 of 98.6% and 66% as opposed to 86.1% and 39% for YOLOv7. When comparing the detected box to the ground truth bounding box at an IOU of 0.5, the mAP values demonstrate how well the model detects an object within a frame. When comparing the mAP@0.5 of YOLOv5s to YOLOv7, there is a 12.5% difference, which indicates how well the model detects items correctly and precisely when compared to ground truth objects. The mAP@0.5:0.95 also shows superior performance for YOLOv5s in comparison with YOLOv7, with a marginal 2.7% difference in average mAP at different thresholds. All performance indicators show that the YOLOv5s model outperforms the YOLOv7 model, except for recall score during testing. The investigations suggest that YOLOv5s performs better than YOLOv7 in terms of detection accuracy, precision, and recall, particularly when utilized in production, as indicated by the testing results (Table 3).

DISCUSSION

The experimentation it is found that the classification accuracy is differed from epoch to epoch. From the analysis the YOLOv5s and YOLOv7 showed the almost similar behaviour according to epochs. But the YOLOv5s achieved the 98.6% classification accuracy at 350 epochs, whereas YOLOv7 obtained 86.1% at 110. Even the YOLOv7 achieved the higher accuracy at lower epochs the mAP is very lower compared with YOLOv5s. Further the YOLOv5s model achieves 140 frames per second (fps) and YOLOv7 fps is 290. The greater frame rate in YOLOv7 results in a decreased accuracy of 86.1%. This study is compared to the work of Haitong Pang, et al. who achieved 92.86% accuracy with YOLOv4, while the current study achieved 5.74% higher accuracy using YOLOv5s. According to Tetila et al., (2021), the pest identification accuracy of using YOLOv3 is 93%, while the suggested study achieved a 5.6% better accuracy. The research results of Jayasuriya et al., (2021) demonstrate that when VGG-19 is enhanced with deblurring, it achieves an impressive accuracy of 97.74% in accurately diagnosing flaws. When the VGG-16 model was enhanced with the Canny filter, it obtained a remarkable accuracy of 99.35% in accurately detecting pest infestations. Moreover, when combined with EfficientDet, VGG-19 demonstrated an impressive accuracy rate of 99% in disease identification. However, when compared to deep learning systems that use the You Only Look Once (YOLO) algorithm, its detection capabilities are below average (Jiang et al., 2022; Gillani et al., 2022). In addition, the current study presents a novel link between epochs and accuracy, which demonstrated a more significant influence on the parameter mAP that was obtained as a result of the research. When compared to the findings of earlier studies, the findings of YOLOv5 on the detection of chilli pests are, in general, quite impressive in terms of the accuracy of detection. YOLOv5 is recommended as the best detector for accurately recognizing pests in well-balanced multi-class datasets, outperforming YOLOv7, VGG-16 (~92.7%), and VGG-19 (~84.24%) deep learning architectures. In addition, the findings of this research shed light on a previously unknown connection between epochs and precision. A combination of detecting pests and explaining the impact of epochs on the mAP that is produced as a result is described in the current work, which is a unique piece of work because it describes the combination.

CONCLUSIONS

Chilli is a highly sought-after horticultural crop in South Asia. Farmers are suffering losses due to a significant bug infestation on their chilli crop. Early pest detection is a solution that can improve crop productivity. The current study primarily centers on pest identification in chilli crops utilizing the Convolutional Neural Network architecture of YOLOv5s and YOLOv7. The study examined three chilli pests: Black Thrips, Red Mites, and White Flies, known for causing significant damage to chilli crop leaves. The study generated a new pest dataset and used CNN-based YOLO v5 and v7 versions for pest detection. The v5 algorithm performs better than v7 for all three types of chilli pests. However, the results indicate that detection performance is better in version 7 and worse in version 5 at lower epochs. The computation time is longer in v5 compared to v7 since the frames per second (fps) are higher in v7 and lower in v5. The study shows that the mAP performance of YOLOv5s is better than that of YOLOv7. The present study reveals that YOLOv5 is recommended for Chilli pest detection with higher accuracy than existing VCC-16 and VCC-19. The current study is limited to only pests data and larvae detection is yet be incorporated.

REFERENCES

1. Agustian, I., Faurina, R., Ishak, S. I., Utama, F.P., Dinata, K., Daratha, N. 2023. Deep learning pest detection on Indonesian red chili pepper plant based on fine-tuned YOLOv5. International Journal of Advances in Intelligent Informatics, 9(3). https://doi.org/10.26555/ijain.v9i3.864
2. Alsubaei, F.S., Almazroi, A.A., Ayub, N. 2024. Enhancing phishing detection: A novel hybrid deep learning framework for cybercrime forensics. IEEE Access. https://doi.org/10.1109/ACCESS.2024.3351946
3. Amara, S.J., Yamini, S., Sumathi, D. 2023. Pest Detection Using YOLO V7 Model. In International Conference on Data Science and Network Engineering, 225–235. Singapore: Springer Nature Singapore. https://doi.org/10.1007/978-981-99-6755-1
4. Ameen, Y.A., Badary, D.M., Abonnoor, A.E.I., Hussain, K.F., Sewisy, A.A. 2023. Which data subset should be augmented for deep learning? a simulation study using urothelial cell carcinoma histopathology images. BMC bioinformatics, 24(1), 75. https://doi.org/10.1186/s12859-023-05199-y.
5. Amrani Abderraouf, Sohel Ferdous, Diepeveen Dean, Murray David, Jones Michael G. K. 2023. Insect detection from imagery using YOLOv3-based adaptive feature fusion convolution network. Crop & Pasture Science 74, 615–627. https://doi.org/10.1071/CP21710
6. Blanchy, G., Saneiyan, S., Boyd, J., McLachlan, P., Binley, A. 2020. ResIPy, an intuitive open-source software for complex geoelectrical inversion/modeling. Computers & Geosciences, 137, 104423. https://doi.org/10.1016/j.cageo.2020.104423
7. Carreón-Anguiano, K.G., Islas-Flores, I., Vega-Arreguín, J., Sáenz-Carbonell, L., Canto-Canché, B. 2020. EffHunter: A tool for prediction of effector protein candidates in fungal proteomic databases. Biomolecules, 10(5), 712. https://doi.org/10.3390/biom10050712
8. Ceballos, F., Kannan, S., Kramer, B. 2020. Impacts of a national lockdown on smallholder farmers' income and food security: Empirical evidence from two states in India. World Development, 136, 105069. https://doi.org/10.1016/j.worlddev.2020.105069
9. Chen, C., Liang, Y., Zhou, L., Tang, X., Dai, M. 2022. An automatic inspection system for pest detection in granaries using YOLOv4. Computers and Electronics in Agriculture, 201, 107302. https://doi.org/10.1016/j.compag.2022.107302
10. Chen, J. W., Lin, W.J., Cheng, H.J., Hung, C.L., Lin, C.Y., Chen, S.P. 2021. A smartphone-based application for scale pest detection using multiple-object detection methods. Electronics, 10(4), 372. https://doi.org/10.3390/electronics 10040372
11. Chen, W., Modi, D., Picot, A. 2023. Soil and phytomicrobiome for plant disease suppression and management under climate change: A review. Plants, 12(14), 2736. https://doi.org/10.3390/plants12142736
12. Chen, Y. 2024. The Investigation of Performance Comparison for VGG, YOLO, and DINO in Image Classification. Highlights in Science, Engineering and Technology, 85, 984–990. https://doi.org/10.54097/9bgem219
13. Dai, M., Dorjoy, M.M.H., Miao, H. and Zhang, S. 2023. A new pest detection method based on improved YOLOv5m. Insects, 14(1), 54. https://doi.org/10.3390/ insects14010054.
14. Dhiman, P., Kaur, A., Balasaraswathi, V.R., Gulzar, Y., Alwan, A.A., Hamid, Y. 2023. Image acquisition, preprocessing and classification of citrus fruit diseases: A systematic literature review. Sustainability, 15(12), 9643. https://doi.org/10.3390/su15129643
15. Dong, Q., Sun, L., Han, T., Cai, M., Gao, C. 2024. PestLite: A Novel YOLO-Based Deep Learning Technique for Crop Pest Detection. Agriculture, 14(2), 228. https://doi.org/10.3390/agriculture14020228
16. Dong, S., Teng, Y., Jiao, L., Du, J., Liu, K., Wang, R. 2024. ESA-Net: An efficient scale-aware network for small crop pest detection. Expert Systems with Applications, 236, 121308. https://doi.org/10.1016/j.eswa.2023.121308

17. Gil, J.D.B., Reidsma, P., Giller, K., Todman, L., Whitmore, A., van Ittersum, M. 2019. Sustainable development goal 2: Improved targets and indicators for agriculture and food security. Ambio, 48(7), 685–698. https://doi.org/10.1007/s13280-018-1101-4
18. Gillani, I.S., Munawar, M.R., Talha, M., Azhar, S., Mashkoor, Y., Uddin, M., Zafar, U. 2022. Yolov5, yolo-x, yolo-r, yolov7 performance comparison: A survey. Artificial Intelligence and Fuzzy Logic System, 17–28. https://doi.org/10.5121/csit.2022.121602
19. Guo, Q., Wang, C., Xiao, D., Huang, Q. 2023. Automatic monitoring of flying vegetable insect pests using an RGB camera and YOLO-SIP detector. Precision Agriculture, 24(2), 436–457. https://doi.org/10.1007/s11119-022-09952-w
20. Guo, Q., Wang, C., Xiao, D., Huang, Q. 2024. A lightweight open-world pest image classifier using ResNet8-based matching network and NT-Xent loss function. Expert Systems with Applications, 237, 121395. https://doi.org/10.1016/j.eswa.2023.121395
21. Gupta, A., Nahar, P. 2023. Classification and yield prediction in smart agriculture system using IoT. Journal of Ambient Intelligence and Humanized Computing, 14(8), 10235–10244. https://doi.org/10.1007/s12652-021-03685-w
22. Halgamuge, M.N., Nirmalathas, A. 2017. Analysis of large flood events: Based on flood data during 1985–2016 in Australia and India. International Journal of Disaster Risk Reduction, 24, 1–11. https://doi.org/10.1016/j.ijdrr.2017.05.011
23. Hatanaka, M., Konefal, J., Strube, J., Glenna, L., Conner, D. 2022. Data-driven sustainability: Metrics, digital technologies, and governance in food and agriculture. Rural Sociology, 87(1), 206–230. https://doi.org/10.1111/ruso.12415
24. Horowitz, A.R., Ghanim, M., Roditakis, E., Nauen, R., Ishaaya, I. 2020. Insecticide resistance and its management in Bemisia tabaci species. Journal of Pest Science, 93(3), 893–910. https://doi.org/10.1007/s10340-020-01210-0
25. Huang, Y., He, J., Liu, G., Li, D., Hu, R., Hu, X., Bian, D. 2023. YOLO-EP: a detection algorithm to detect eggs of Pomacea canaliculata in rice fields. Ecological Informatics, 77, 102211. https://doi.org/10.1016/j.ecoinf.2023.102211
26. Huo, D., Malik, A.W., Ravana, S.D., Rahman, A.U., Ahmedy, I. 2024. Mapping smart farming: Addressing agricultural challenges in data-driven era. Renewable and Sustainable Energy Reviews, 189, 113858. https://doi.org/10.1016/j.rser.2023.113858
27. Jayasuriya, K., Kotapolage, D., Gamage, S., Haddela, P., Pemadasa, N. 2022. Plant Stresses and Pest Attack Detection Using Convolutional Neural Networks with Advance Preprocessing Techniques in Chili Plants. In Proceedings of the Future Technologies Conference (FTC) 2021, 2, 17–33). Springer International Publishing.
28. Jiang, P., Ergu, D., Liu, F., Cai, Y., Ma, B. 2022. A Review of Yolo algorithm developments. Procedia computer science, 199, 1066–1073. https://doi.org/10.1016/j.procs.2022.01.135
29. Khan, W., Jamshed, M., Fatima, S. 2020. Contribution of agriculture in economic growth: A case study of West Bengal (India). Journal of Public Affairs, 20(2), e2031. https://doi.org/10.1002/pa.2031
30. Kumar, V., Khan, M. R., Walia, R.K. 2020. Crop loss estimations due to plant-parasitic nematodes in major crops in India. National Academy Science Letters, 43(5), 409–412. https://doi.org/10.1007/s40009-020-00895-2
31. Legaspi, K.R.B., Sison, N.W.S., Villaverde, J.F. 2021. Detection and classification of whiteflies and fruit flies using YOLO. In 13th International Conference on Computer and Automation Engineering (ICCAE), IEEE, 14. https://doi.org/10.1109/ICCAE51876.2021.9426129
32. Li, D., Ahmed, F., Wu, N., Sethi, A.I. 2022. Yolo-JD: A Deep Learning Network for jute diseases and pests detection from images. Plants, 11(7), 937. https://doi.org/ 10.3390/plants11070937
33. Lippi, M., Bonucci, N., Carpio, R.F., Contarini, M., Speranza, S., Gasparri, A. 2021. A yolo-based pest detection system for precision agriculture. In 2021 29th Mediterranean Conference on Control and Automation (MED), 342–347, IEEE. https://doi.org/10.1109/MED51440.2021.9480344
34. Lippi, M., Carpio, R.F., Contarini, M., Speranza, S. and Gasparri, A. 2022. A data-driven monitoring system for the early pest detection in the precision agriculture of hazelnut orchards. IFAC-Papers On Line, 55(32), 42–47. https://doi.org/10.1016/j.ifacol.2022.11.112
35. Liu, J., Wang, X. 2020. Tomato diseases and pests detection based on improved Yolo V3 convolutional neural network. Frontiers in plant science,11, 521544. https://doi.org/10.3389/fpls.2020.00898
36. Liu, L., Wang, R., Xie, C., Yang, P., Wang, F., Sudirman, S., Liu, W. 2019. PestNet: An end-to-end deep learning approach for large-scale multi-class pest detection and classification. IEEE Access, 7, 45301–45312. https://doi.org/10.1109/access.2019.2909522
37. Lodaya, J.P., Suthar, M., Patel, H.C., Sisodiya, D.B., Acharya, R.R., Raval, A.T., Mohapatra, A.R. 2022. Status of invasive species of thrips, Thrips parvispinus (Karny) infesting chilli grown in middle Gujarat. The Pharma Innovation Journal 2022, 11(3), 1298–1302. https://www.thepharmajournal.com/archives/2022/vol11issue3/PartQ/11-3-144-227.pdf
38. Lyu, S., Zhou, X., Li, Z., Liu, X., Chen, Y., Zeng, W. 2023. YOLO-SCL: a lightweight detection model for citrus psyllid based on spatial channel interaction. Frontiers in Plant Science, 14, 1276833. https://doi.org/10.3389/fpls.2023.1276833

39. Mushi, G.E., Di Marzo Serugendo, G., Burgi, P.Y. 2022. Digital technology and services for sustainable agriculture in Tanzania: A literature review. Sustainability, 14(4), 2415. https://doi.org/10.3390/su14042415
40. Nanditha, J.S., Kushwaha, A.P., Singh, R., Malik, I., Solanki, H., Chuphal, D.S., Mishra, V. 2023. The Pakistan flood of August 2022: causes and implications. Earth's Future, 11(3), e2022EF003230. https://doi.org/10.1029/2022EF003230
41. Onler, E. 2021. Real time pest detection using YOLOv5. International Journal of Agricultural and Natural Sciences, 14(3), 232–246. Retrieved from https://www.ijans.org/index.php/ijans/article/view/550
42. Qi, F., Wang, Y., Tang, Z., Chen, S. 2023. Real-time and effective detection of agricultural pest using an improved YOLOv5s network. Journal of Real-Time Image Processing, 20(2), 33. https://doi.org/10.1007/s11554-023-01264-0
43. Santamaria, M.E., Arnaiz, A., Rosa-Diaz, I., González-Melendi, P., Romero-Hernandez, G., Ojeda-Martinez, D.A., Diaz, I. 2020. Plant defenses against Tetranychus urticae: mind the gaps. Plants, 9(4), 464. https://doi.org/10.3390/plants9040464
44. Singh, D.P. 2023. Concept and Practices of IPM in Relation to Different Crops and Cropping Systems. In Integrated Pest Management in Diverse Cropping Systems 91–109. Apple Academic Press. https://doi.org/10.1201/9781003304524
45. Singh, S., Kansal, M.L. 2022. Cloudburst—a major disaster in the Indian Himalayan states. Civil Engineering for Disaster Risk Reduction, Springer Tracts in Civil Engineering, 115–126. https://doi.org/10.1007/978-981-16-5312-4_9
46. Sireesha, K.,. Prasanna B.V.L., Vijaya Lakshmi, T., and Reddy, R.V.S.K. 2021. Outbreak of invasive thrips species Thrips parvispinus in chilli growing areas of Andhra Pradesh. Insect Environment, 24(4), 514–519.
47. Soeb, M.J.A., Jubayer, M.F., Tarin, T.A., Al Mamun, M.R., Ruhad, F.M., Parven, A., Mubarak, N.M., Karri, S.L. and Meftaul, I.M. 2023. Tea leaf disease detection and identification based on YOLOv7 (YOLO-T). Scientific reports, 13(1), 6078. https://doi.org/10.1038/s41598-023-33270-4
48. Sun, L., Cai, Z., Liang, K., Wang, Y., Zeng, W., Yan, X. 2024. An intelligent system for high-density small target pest identification and infestation level determination based on an improved YOLOv5 model. Expert Systems with Applications, 239, 122190. https://doi.org/10.1016/j.eswa.2023.122190
49. Sun, L., Liang, K., Wang, Y., Zeng, W., Niu, X., Jin, L. 2024. Diagnosis of tomato pests and diseases based on lightweight CNN model. Soft Computing, 28(4), 3393–3413. https://doi.org/10.1007/s00500-023-08631-w
50. Tetila, E.C., da Silveira, F.A.G., da Costa, A.B., Amorim, W.P., Astolfi, G., Pistori, H., Barbedo, J.G.A. 2024. YOLO performance analysis for real-time detection of soybean pests. Smart Agricultural Technology, 7, 100405. https://doi.org/10.1016/j.atech.2024.100405
51. Tian, Y., Wang, S., Li, E., Yang, G., Liang, Z., Tan, M. 2023. MD-YOLO: Multi-scale Dense YOLO for small target pest detection. Computers and Electronics in Agriculture, 213, 108233. https://doi.org/10.1016/j.compag.2023.108233
52. Towfek, S.K., Khodadadi, N. 2023. Deep Convolutional Neural Network and Metaheuristic Optimization for Disease Detection in Plant Leaves. Journal of Intelligent Systems and Internet of Things, 10(1), 66–75. https://doi.org/10.54216/JISIoT.100105
53. Wang, X., Zhang, S., Zhang, T. 2024. Crop insect pest detection based on dilated multi-scale attention U-Net. Plant Methods, 20(1), 34. https://doi.org/10.1186/s13007-024-01163-w
54. Wei, M., Zhan, W. 2024. YOLO_MRC: A fast and lightweight model for real-time detection and individual counting of Tephritidae pests. Ecological Informatics, 79, 102445. https://doi.org/10.1016/j.ecoinf.2023.102445
55. Wen, C., Chen, H., Ma, Z., Zhang, T., Yang, C., Su, H., Chen, H. 2022. Pest-YOLO: A model for large-scale multi-class dense and tiny pest detection and counting. Frontiers in Plant Science, 13, 973985. https://doi.org/10.3389/fpls.2022.973985
56. Yang, S., Xing, Z., Wang, H., Dong, X., Gao, X., Liu, Z., Zhao, Y. 2023. Maize-YOLO: a new high-precision and real-time method for maize pest detection. Insects, 14(3), 278. https:// doi.org/10.3390/insects14030278
57. Zhang, Y., Ma, B., Hu, Y., Li, C., Li, Y. 2022. Accurate cotton diseases and pests detection in complex background based on an improved YOLOX model. Computers and Electronics in Agriculture, 203, 107484. https://doi.org/10.1016/j.compag.2022.107484
58. Zhu, L., Li, X., Sun, H., Han, Y. 2024. Research on CBF-YOLO detection model for common soybean pests in complex environment. Computers and Electronics in Agriculture, 216, 108515. https://doi.org/10.1016/j.compag.2023.108515
59. Zhu, R., Hao, F., Ma, D. 2023. Research on Polygon Pest-Infected Leaf Region Detection Based on YOLOv8. Agriculture, 13(12), 2253. https://doi.org/10.3390/ agriculture13122253