SCIENTIFIC CULTURE
www.sci-cult.com

SCIENTIFIC CULTURE, Vol. 12, No. 4, (2026), pp. 11790-11805
Open Access. Online & Print

DOI: 10.5281/zenodo.124261118

AI-POWERED PRECISION AGRICULTURE SYSTEM FOR CHILLI CROP PEST DETECTION, LOCALIZATION, AND DISEASE CLASSIFICATION

Chaitali Darode[1], Dr. Abhay Ramakant Kasetwar[2]

[1,2]S.B. Jain Institute of Technology, Management and Research, Nagpur, Maharashtra

Received: **19/11/2025**
Accepted: **11/04/2026**

Corresponding Author: Chaitali Darode
(*chaitalidarode@gmail.com***)**

ABSTRACT

This paper outlines a smart AI-based system that can be used to detect and manage pests in chilli plants at an early stage using the deep learning methodology. The suggested structure combines disease diagnosis and pest identification to facilitate accuracy agriculture. ResNet50 and EfficientNet-B0 are transfer learning models used in learning the leaf diseases, whereas YOLOv8 is used in pest detection and localization in real-time. The real-field images are processed by the system undergoing preprocessing procedures such as resizing, normalization, and augmentation of the images to enhance model robustness. According to experimental results, the classification accuracy is very high, and EfficientNet-B0 and AlexNet can attain up to 98% accuracy, whereas YOLOv8 has a good ability to detect objects in the conditions of a complex field. The model will provide a targeted and efficient pest control because it concentrates on the key pests such as fruit borers and cutworms. In general, the system minimizes reliance on manual surveillance and overuse of pesticides, which adds to sustainable agriculture and enhanced crop yield.

KEYWORDS: *Deep Learning, Pest Detection, Chilli Crop, YOLOv8, Disease Classification, Precision Agriculture*

1. INTRODUCTION

Chilli (Capsicum annuum L.) is a type of commercial spice and vegetable crop that is produced in tropical and subtropical climates, and the crop is a vital part of agricultural trade in the world as well as farmers subsistence [1]. It is grown in large quantities fresh, dried and processed, and thus its quality and yield are very crucial to the domestic as well as export markets. Nonetheless, the production of chilli is very challenging with the problems of insect pests which have direct impacts on the plant vitality, quality of fruits and the overall productivity [2] [3]. Insect pests are one of the most common forms of biotic stressors, which cause a loss in yield especially at sensitive growth stages such as flowering and fruit development as a slight damage can cause huge financial losses [4]. Out of the vast number of pests which infest the chilli crops, the fruit borer (Helicoverpa armigera) is regarded as the most devastating as it directly feeds on the growing fruit. The larvae pierced the fruit tissues leading to internal damages that are not easily noticeable at a tender age, but make the produce unmarketable [5]. Besides the fruit borers, cutworms (Agrotis spp.) are a major threat to the young plants of chilli in their initial stage of growth since they cut seedlings and young stems at the ground level often leading to the total loss of the plant. These pests have a nocturnal and hidden feeding habit, and therefore, with visual observation, early detection is hard since visual observation is not the only method of detecting their presence and thus, the infestation spreads quickly to the fields [6]. The traditional pest management methods applied in the rearing of chilli are based on manual field scouting and the experience of the farmers to detect the presence and the intensity of pests. Although the method has been popular decades ago, it is labor-based, time-consuming, and prone to subjectivity-related errors [7]. In extensive farming, it is no longer feasible to monitor each plant regularly making it more probable to be spotted late [8]. Consequently, they tend to apply pesticides indiscriminately or preventively even without proper identification of the pests, thus, resulting into high cost of production, pesticide resistance, air pollutions, and adverse effects on non-target organisms and soils [9] [10]. The shortcomings of the conventional pest monitoring systems have heightened the need to have intelligent and automated systems that can capture pests at an early infestation stage [11]. Over the past few years, deep learning (DL) and Artificial Intelligence (AI) methods have demonstrated a promising future in revolutionizing the process of agricultural pest management [12]. Deep learning models, especially convolutional neural networks and object detection systems can learn sophisticated visual cycles and differentiate small insects in natural backgrounds full of debris [13]. These abilities render them well adapted in the detection of chewing pests like fruit borers and cutworms when images are taken in the real-field conditions [14].

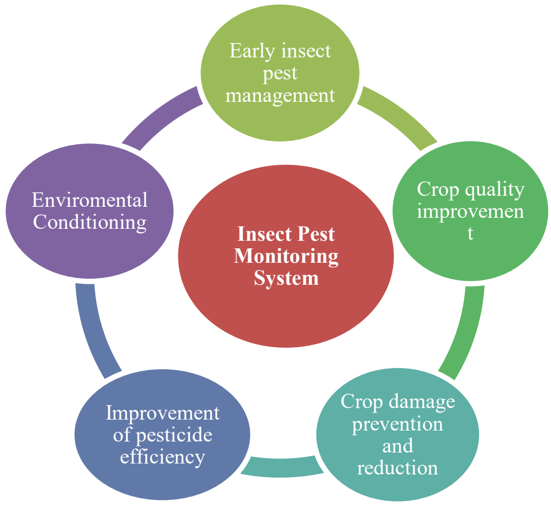

Figure 1: Benefits of an insect pest monitoring system in agriculture.

Object detection algorithms like the You Only Look Once (YOLO) family have shown impressive results in real-time agricultural scene detectors because of their high speed and accuracy [15]. These models are capable of localizing pests by producing bounding boxes and class labels with one forward pass, and thus find and track them in time [16]. Such models could be used on chilli crops to identify the presence of fruit bores and cutworms in the fruit, stems, and soil-levels using images of the crops, and thus, early detection of the infestations is made [17]. This early detection also helps in accuracy in eradicating pests, as control measures can only be used in the affected areas and a great deal of chemicals are saved, making the use of chemicals much more sustainable. Here the current work suggests the use of an AI-based pest detector and eliminator with a specific interest in fruit borer and cutworm attacks on chilli plants [18]. The proposed system will help decrease the computational complexity, increase the reliability of detection by limiting the scope to two high-impact pests, and enhance the viability of the system in the field [19]. This system is meant not just to locate and detect pests but also to assist in making decisions in time to eradicate them without causing too much damage to crops and the environment [20]. This is a focused strategy that helps in developing sustainable chilli production through encouraging efficient and ecologically friendly pest management. Moreover, the growing supply of low-cost imaging systems, mobile phones, and edge-computing systems has generated a novel option of executing AI-based pest management solutions directly on farms [21, 22]. Farmers are now able to take actual pictures of the chilli plants and obtain immediate responses on the existence and degree of the pests without involving the expertise of the experts. By combining pest detection with the use of deep learning and the eradication-centered decision support, it is possible to provide timely recommendations, including targeted spraying times, appropriate control strategies, and prevention steps, depending on the presence of the fruit borer or cutworm cases [23]. This strategy fills the divide between a pest detection and a response to the threat, changing the traditional reactive pest management to a proactive and methodical strategy that improves crop protection, mitigates yield losses, and promotes sustainable agriculture [24]. Here are the research objectives as shown below:

I. To develop an AI-based framework for automated chilli crop monitoring by integrating disease classification and pest detection using deep learning techniques.
II. To preprocess and prepare chilli leaf and pest image datasets using resizing, normalization, augmentation, and train–test splitting for robust model training.
III. To classify chilli leaf diseases into five categories using transfer learning models such as ResNet50 and EfficientNet-B0.
IV. To detect and localize major chilli pests using YOLOv8-based object detection with bounding box prediction.
V. To evaluate the proposed system performance using standard metrics such as accuracy, precision, recall, and F1-score, and generate pest eradication/control recommendations to support precision agriculture decisions.

2. Review of Literature

The detection of insect pests in agricultural scenes poses special problems because of the presence of clutter, a changing light source, occlusions by the foliage, and the size of the pests in relation to the plant structures. Such obstacles are especially notable in that of chilli crops where the pests that beset them like fruit borers and cutworms have a hidden feeding habit and are only partially visible in the course of infestation. Conventional image-processing methods fail to work in these conditions, which is why the use of deep learning-based object-detection models that are able to learn discriminative features as of real-field images is encouraged. Recent research has focused on the point that the accuracy of pest detection is highly influenced by occlusion, scale change and irregular backgrounds thus agricultural pest monitoring is no easy computer vision task.

Research done within the past five years shows that the deep convolutional neural networks have enhanced considerably the pest detection performance because they learn hierarchical visual features directly on real-field images. Leite et al. (2025) [25] have highlighted the fact that the pest-specific visual complexity particularly in fruit borers leads to reduced detection ability by applying generalized classification models. They found that localized object detection methods succeed in classification without the whole image since the model can concentrate on the areas with pests instead of the overall plant image. These points were closely observed by Odounfa et al. (26) [26], who have shown that occlusion and partial visibility are the conditions that result in the highest rates of false detection in monitoring chilli pests, especially when they are feeding internally or are near stem junctions. Single-stage object detectors like YOLO have also become of interest to researchers to overcome these obstacles because they can be used to conduct real-time object detection with high spatial resolution. Hamim et al. (2024) [27] provided a comparative study on several deep learning architectures used to detect chilli pests, which indicated that the models based on the YOLO detected fruit borers with a higher mean average precision than the models using conventional CNN classifiers. Their results were in agreement that bounding-box localization is critical in the detection of pests that lead to localized damage. Kanaparthi et al. (2023) [28] also confirmed this strategy by fine-tuning YOLOv5 on chilli pest images showing that the method is more robust to background distraction and changes in lighting with large amounts of data.

Studies have also found that deep learning models which are trained on various real-field data can be useful in learning discriminative texture and shape features of pests that attack fruits. Agustian et al. (2024) [29] indicated that the detection rates of the insects that were responsible of boring fruit exceeded 99 percent when using the YOLO-based frameworks, which underscores the power of multi-scale feature extraction in identifying the morphology of pests. They note in their work that the initial localization of borers is the most important factor to avoid internal fruit damage, which is why object detection models are still relevant in pest eradication systems. Conversely, the method of identifying cutworms is still under-researched because the insects are active at night and feed on the ground. Chakrabarty et al. (2025) [30] established that degradation of image quality has a critical impact on detection confidence of pests at soil-level and suggested an image enhancement pipeline that enhanced more reliable detection of partially intact pests like cutworms. Jia et al. (2024) [31] also noted that the pests that induce damage at the stem level cannot be grouped based on global classification and instead demanded spatial sensitivity in detection schemes to identify cutworms.

In addition to detection accuracy, recent studies have emphasized on combining pest detection and eradication-oriented decision support. The study by Nurokhman et al. (2024) [32] revealed that real-time alerts and early pest detection could greatly decrease the loss of yield and the response time. But such systems tend to be generalizing the pests and not pest specific to eradicate them. Balasubramaniam et al. (2022) [33] highlighted the fact that spatial localization is the only way to achieve precision pest management because of the ability to selectively spray and minimise excessive pesticide application especially in localised pests like fruit borers and cutworms. In addition, Islam et al. (2024) [34] introduced a machine learning-driven forecasting system of crops (chilli disease), and pest forecasting with the accuracy of 0.90, whereas Islam et al. (2021) [34] provided the UAV-based prediction of weeds in chilli fields using classical ML models with 96 percent accuracy, which used Random Forest. The most recent evolution is a YOLO-Pepper model, that will be used in edge-based smart farming systems, proposed by Wang et al. (2025) [35], which is a refined version of the YOLOv10n-based model that detects pepper pest/disease with 94.26 mAP at 0.5 and 115.26 FPS and 2.51M parameters. Combining these researches, the existence of an AI-based pest detecting and eliminating solution in chilli crops will contribute to the provision of adequate detection, real-time speed, and coverage in the fields. On the whole, the systematic review of the up-to-date literature demonstrates that although deep learning-based object detection models have succeeded significantly in the agricultural pests detection, the majority of the existing studies are essentially concerned with the detection and classification efficiency. Little emphasis has been placed on the development of end-to-end systems that will combine precise identification of high-impact pests, including fruit borers and cutworms with decision-making that will focus on eradication. Moreover, the issues concerning real-field generalization, initial pest observation, and specific control plan solutions are not properly tackled. These loopholes indicate the need to have a dedicated, pest-specific AI model, which can be used in the detection and successful elimination of pests in the cultivation of chilli crops.

3. RESEARCH METHODOLOGY

This section shows the entire workflow of the suggested AI-based system to classify chilli disease and identify pests. Figure 2 presents the general research flow with collecting data to use in the study with the Chilli Plant Disease Dataset and the IP102 pest dataset, then pre-processing data, feature extraction, and finally, splitting the data. ResNet50 and a hybrid ResNet50 + EfficientNet-B0 ensemble model is used to classify chilli leaf disease to improve the prediction accuracy. To detect and localize the pests, they use YOLOv8 and detect the pests in the form of bounding boxes. Lastly, standard metrics of system performance are analyzed in the form of accuracy, precision, recall, and F1-score.

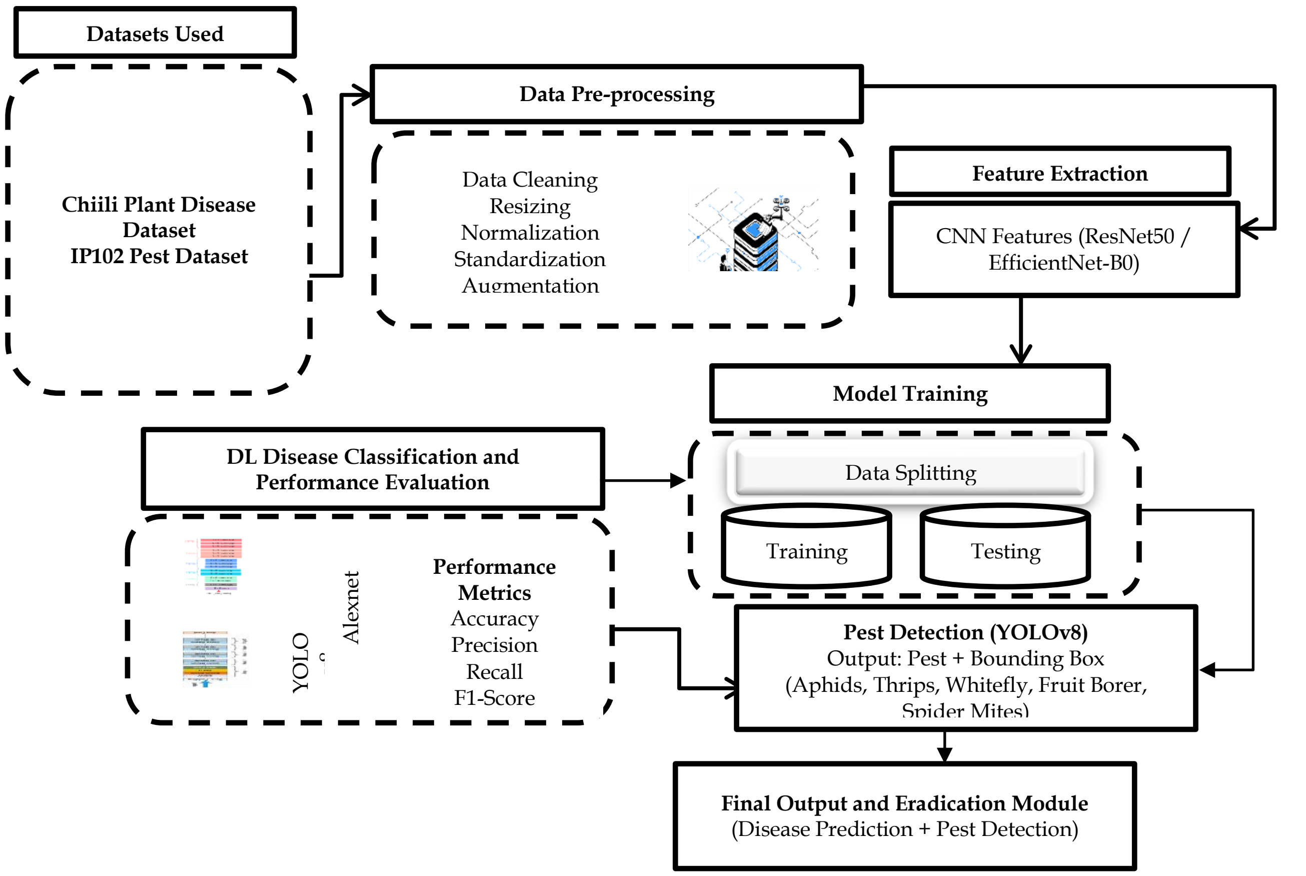

Figure 2: Proposed Methodology

3.1 Datasets Used

- **Chilli Plant Disease Dataset**

Chilli Plant Disease Dataset [36] is a publicly owned image dataset, which is utilized in the identification and classification of diseases in chilli crops. It includes RGB pictures of chilli plants and leaves under real-field and natural conditions with differences in the light aspects and background complexity and leaf position. They selected five classes in this study namely: Healthy, Leaf Spot, Leaf Curl, Whitefly, and Yellowish. These images uphold the supervised learning model of CNN and transfer learning models to identify the symptoms of diseases based on leaves patterns. This data can be applied to smart farming since it allows timely detection of diseases and tracking of crops. Figure 3 presents the sample images of the five-chilli leaf disease. Table 1 shows the Class-wise Distribution of Chilli Plant Disease Dataset.

Table 1: Class-wise Distribution of Chilli Plant Disease Dataset

No.	Class Name	No. of Images
1	Healthy	800
2	Leaf Spot	750
3	Leaf Curl	700
4	Whitefly	650
5	Yellowish	600
Total	–	**3500**

Figure 3: Sample images of the five chilli leaf disease classes.

- **IP102 pest dataset**

The IP102 pest dataset [37] is a large-scale benchmark dataset developed for agricultural insect pest recognition. Around 75,000 RGB images were acquired from the natural background of crop fields under various light conditions. It includes 102 classes of insect pests with labeled annotations, carried out for pest recognition tasks. For this work, they used five categories from IP102 that are relevant to chilli in order to create a subset for training and testing of the pest detection module. Table 2 shows Selected Pest Classes from IP102 dataset.

Table 2: Selected Pest Classes from IP102

No.	Pest Name	No. of Images
1	Aphids	850
2	Thrips	780
3	Whitefly	720
4	Fruit Borer	650
5	Spider Mites	600
Total	**—**	**3600**

3.2 Data Pre-processing

- **Data Cleaning and Filtering**

In real databases, a lot of images can be repeated, blurred, or improperly taken because of the movement of the camera and inaccurate focusing. They are such samples which serve as outliers and add to the difficulty of learning by the model. Deep learning models are data-driven; therefore, poor quality samples can compel the model to learn false patterns decreasing overall accuracy. Data cleaning is used to guarantee the features in feature learning are based on meaningful samples.

Let the original dataset be represented as:

$$D = \{(x_i, y_i)\}_{i=1}^{N} \quad (1)$$

where x_i is an image and $y_i$is its class label. After removing noisy samples, the cleaned dataset becomes:

$$D' = \{(x_i, y_i)\}_{i=1}^{M}, M < N \quad (2)$$

This refined dataset improves training reliability and reduces bias.

- **Image Resizing**

Architectures of deep learning like CNNs and YOLO assume a fixed dimensional input since the convolution operation and fully connected layers assume equal size tensors. Resizing can also be used to minimize the cost of computation and implement batch training. In addition to this, the resolution of images is consistent so that the features such as leaf texture, shape of pests, and color patterns are learned in a similar manner throughout the dataset.

If an image of size $(H, W)$is resized to (H', W'), then:

$$x_i' = Resize(x_i, H', W') \quad (3)$$

- **Pixel Normalization**

Normalization is relevant due to the fact that raw pixel values fall between the following range [0 255]. Big values of inputs may result in unstable gradients in the process of backpropagation, which slows the convergence and results in poor optimization. Normalization of pixel values makes the model to be able to train efficiently and the likelihood of gradient explosion is minimized.

The normalized image is computed as:

$$x_{norm} = \frac{x}{255} \quad (4)$$

This converts pixel values into $[0, 1]$, making training smoother and more stable.

- **Standardization**

When the inputs are standardized, the training is enhanced by the fact that the means of the inputs are zero and the variances are unit values. This comes in quite handy when the pretrained weights are used in transfer learning models (ResNet, MobileNet, EfficientNet) and the distribution of inputs is supposed to be standard. It is also useful in ensuring that the optimizer achieve minima more quickly by ensuring feature distributions are uniform.

$$x_{std} = \frac{x-\mu}{\sigma} \quad (5)$$

where $\mu$is mean and $\sigma$is standard deviation of pixel values.

- **Data Augmentation**

Data augmentation was also used to enhance the diversity of the data set and minimize overfitting in training. As the real-field image of chilli can be different because of changes in light, the position of leaves, camera angle, and the size of pests, augmentation allow the model to exhibit better generalization to unseen samples. The methods of creating realistic variations of the original images were random rotation, horizontal and vertical flipping, zooming and adjusting the brightness. This increases strength and overall classification and detection.

3.3 Feature Etraction

In deep learning-based image analysis, feature selection is generally not manual because the model learns the important features from the images by itself. Hence, in this study, feature extraction has been done using CNN and YOLO architectures where the deep layers extract significant patterns like leaf texture, variation in colors for diseases and pests, shapes of bodies of pests as well as edge information.

For Chilli Plant Disease Dataset, a CNN/transfer learning model was used to extract features at different levels or hierarchies. Early convolution layers would represent low-level features such as edges and color gradients while deeper layers would represent high-level features such as patterns of disease lesions and distortions in the veins. The Convolution operation can be mathematically expressed as:

$$F(i,j) = \sum_m \sum_n I(i+m, j+n) \cdot K(m,n)$$

(6)

where I is the input image and K is the convolution kernel.

For the IP102 pest dataset, YOLO extracts spatial features through its convolutional backbone layers that produce feature maps to localize pests; these deep-extracted features are then forwarded onto a detection head responsible for predicting both bounding boxes and classes of pests. This automatic learning of features enhances accuracy in detection while eliminating any need for manual selection methods involving handcrafted features.

3.4 Data Splitting

After performing the data cleaning, resizing, normalization, and augmentation, the two datasets were split into training and testing subsets for an unbiased assessment of the model performance. Data splitting is crucial because it is important that the model is trained on unseen images of plants for an honest assessment of the model's performance, as well as for avoiding overfitting during training of a model on data. In this project, an 80:20 split ratio is considered, which means 80% of images would be used for training the deep learning models, while 20% is set aside for testing of the models developed. The model is split in a balanced manner for equal representation of all disease and pest groups.

3.5 Classification Models

The classification models used in this paper will target the automatic learning and discrimination of visual patterns that are associated with chilli leaf diseases and the presence of pests to real-field images. The hierarchical features such as color variations, texture irregularities, lesion patterns, and shape distortions found on infected leaves are detected using convolutional Neural Network-based architectures, such as AlexNet and transfer learning-based CNN feature extractors YOLOv8. Learned properties are then propagated via full connected layers so as to provide the class labels based on a healthy or diseased label. Simultaneously, the classification unit is closely linked to detection-based deep models to be able to provide high-quality decision-making results under harsh backgrounds, changing light conditions, and obstructions to guarantee high-quality disease detection and pest-sensitive crop control in precision agriculture environments.

- **YOLOv8 architecture**

YOLOv8 (You Only Look Once version 8) is a state-of-the-art the deep-learning model that is commonly used to detect objects in real time [38]. It is also fast and does single forward scan detection, hence it is applicable in agricultural use like pest detection in chili crops. YOLOv8 has a backbone network (extraction of features), neck network (combination of multi-scale features), and the detection head (prediction of bounding boxes and class probabilities) [39].

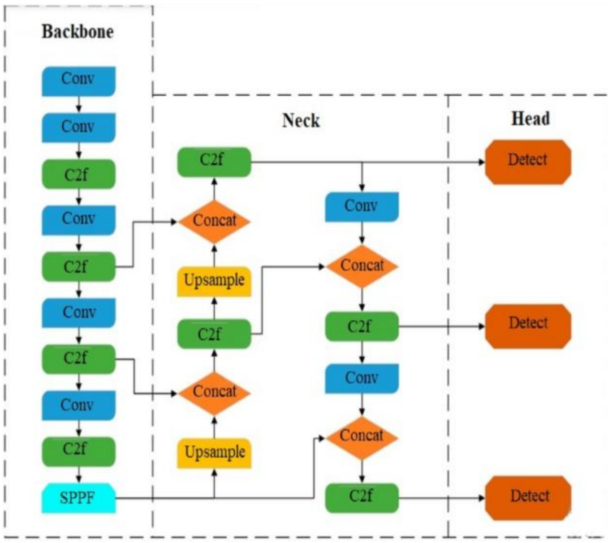

Figure 4: Architecture of YOLOv8 Model [40]

It can efficiently track small bugs such as aphids, thrips and whiteflies even in the field situation with a complicated background. In this work, the pests are localized with the help of YOLOv8 that draws bounding boxes and classifies them, providing a timely decision to eradicate them [40]. The prediction of the bounding box is usually in the form of:

$B = (x, y, w, h)$ (7)

where (x, y) is the box center and (w, h) denote width and height of the detected object.

- **AlexNet**

Another important architecture that contributed to popularizing the use of deep learning in computer vision tasks is AlexNet, a landmark deep convolutional neural network (CNN) architecture [41]. It had the ability to automatically extract hierarchical features of raw images with the use of multiple convolutional layers and pooling and fully connected layers [42]. The AlexNet has five convolutional layers, which identify low- to high-level visual features, including edges, textures, and object parts, and three fully connected layers, which classify objects. Some of the prominent innovations in the model were the application of the Rectified Linear Unit (ReLU) activation function which speeds up the training process, dropout that helps to curb overfitting as well as data augmentation that enhances generalization [43]. AlexNet was trained effectively on GPUs, and was highly effective in image classification on a large scale compared to traditional machine learning methods, which inspired many future CNN architectures in the task of image recognition, object detection, and pattern analysis in computer applications.

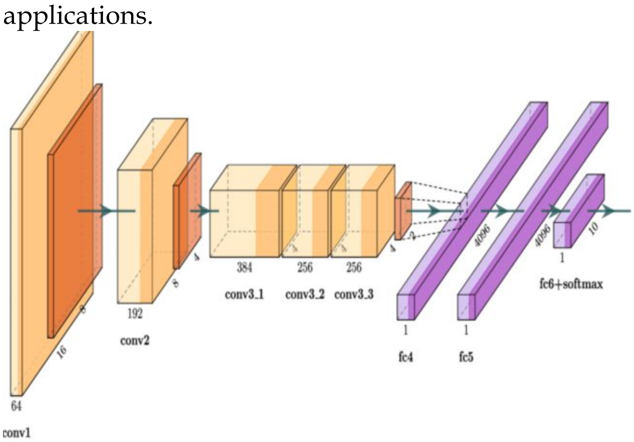

Figure 5: Architecture of Alexnet model [43]

- **YOLOv8 + AlexNet hybrid model**

The proposed hybrid model integrates the real-time object detection capability of the **YOLOv8 architecture** with the strong feature representation power of the **AlexNet convolutional neural network** to enhance pest detection performance in chilli crops [44]. In this hybrid framework, YOLOv8 is employed as the primary detection backbone to localize pests by generating bounding boxes and class probabilities in a single forward pass, enabling fast and accurate identification of fruit borer and cutworm infestations under real-field conditions [45]. To strengthen feature discrimination, intermediate feature maps extracted from the YOLOv8 backbone are refined using AlexNet's deep convolutional layers, which are effective in learning texture, edge, and shape-based patterns critical for distinguishing visually similar pest instances from background foliage [46]. The fusion of YOLOv8's multi-scale spatial features with AlexNet's high-level semantic features improves robustness against occlusion, scale variation, and background noise [47]. This hybrid approach combines the speed and localization accuracy of YOLOv8 with the classification strength of AlexNet, resulting in a more reliable and computationally efficient pest detection model suitable for real-time eradication-oriented precision agriculture applications.

3.6 Performance Metrics

The performance of the proposed system was evaluated using standard metrics such as Accuracy, Precision, Recall, and F1-score.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$$ (8)

$$Precision = \frac{TP}{TP+FP}$$ (9)

$$Recall = \frac{TP}{TP+FN}$$ (10)

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall}$$ (11)

4. Results

4.1 Dataset Class Distribution

Figure 6 shows the class distribution of the dataset, which consists of 3,570 total images. The diseases include Chilli Whitefly, Chilli Yellowish, Chilli Leaf Curl Virus, and Chilli Leaf Spot, of which there are a total of 500 images each (2,000 images), making up approximately 55.6% of the number of images in the total dataset. There are 1,570 total images in the healthy class, which accounts for 44.4% of the number of images in the dataset. There is an equal distribution of classes in the diseased class (25% – 25% – 25% – 25%), however, there are more images of the healthy class than each of the diseased classes, and thus the class imbalance can be considered moderate.

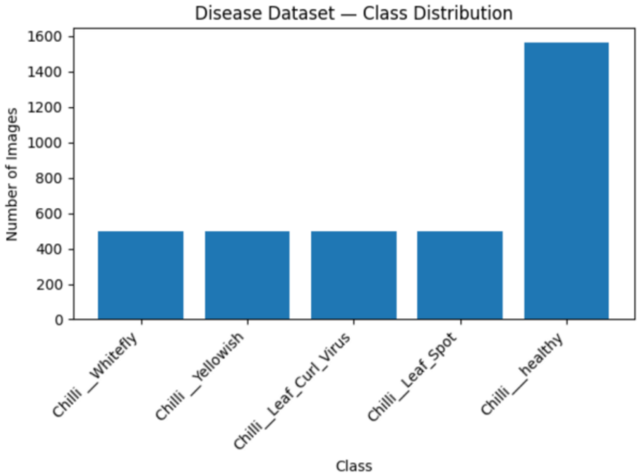

Figure 6: Class distribution of chilli leaf dataset.

Figure 7 shows the class distribution for the pest dataset, which consists of about 1,800 images. The class with the largest number of images is class 23, with about 650 images (≈ 36.1%). The class with the second-largest number of images is class 25, with about 340 images (≈ 18.9%). The class with the third-largest number of images is class 9, with close to 330 images (≈ 18.3%). The class with the third-highest number of images is class 93, with about 305 images (≈ 16.9%). The class with the fewest images is class 33, with about 175 images (≈ 9.7%).

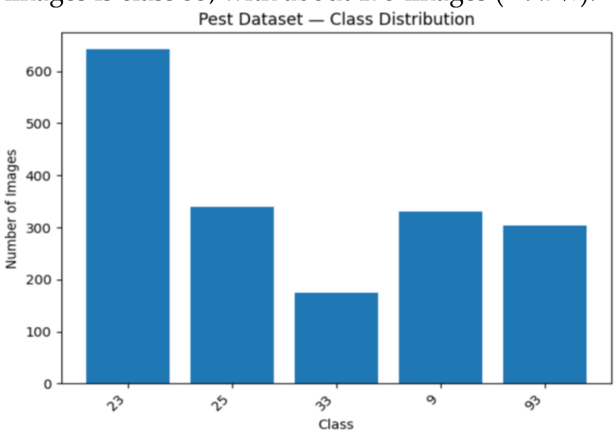

Figure 7: Class distribution of pest dataset.

Representation of Disease Dataset

Figure 8 shows that there is a collection of different types of Images of Chili Pepper Leaves. They can be grouped into five types of plant diseases: bacterial spot, curl virus, leaf spot, wilting, and healthy leaves. Examples of distinguishing features of each type of disease found in the different photos are: discoloration (yellow, brown, and black), spots, curled and/or deformed. The many variations of light source, camera angle, and backdrops make the dataset suitable for training different types of machine training algorithms and deep learning models. The addition of photos that show healthy leaves provides a contrast between healthy and diseased samples, which aids in distinguishing between the two when conducting an analysis. The dataset allows for effective feature extraction and classification by capturing the natural variability in nature, thus supporting the accuracy and generalization rates of automated plant disease detection systems in agriculture.

Figure 8: Sample Images of Chili Leaf Disease Dataset Representing Five Classes

In Figure 9 Machine Learning techniques can be divided into four main categories or paradigms: Supervised, Semi-Supervised, Unsupervised, and Reinforcement Learning. Supervised Learning encompasses both classification and regression tasks. The most common Supervised algorithms include Decision Trees (DT), Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Naïve Bayes (NB), and simple linear regression models. Semi-Supervised Learning uses both labeled and unlabeled data to achieve better results than either would achieve alone. One of the primary goals of Unsupervised Learning is to find hidden patterns within a data set using clustering and dimensionality reduction techniques such as K-means, hierarchical clustering, principal component analysis (PCA), and independent component analysis (ICA). The main focus of Reinforcement Learning is the reward-driven process of making decisions (e.g., through Q-learning and deep Q-networks) based on experiences from previous decisions. In summary, the figure above compares the different learning paradigms of machine learning and shows how they can be used to solve various types of real-world problems.

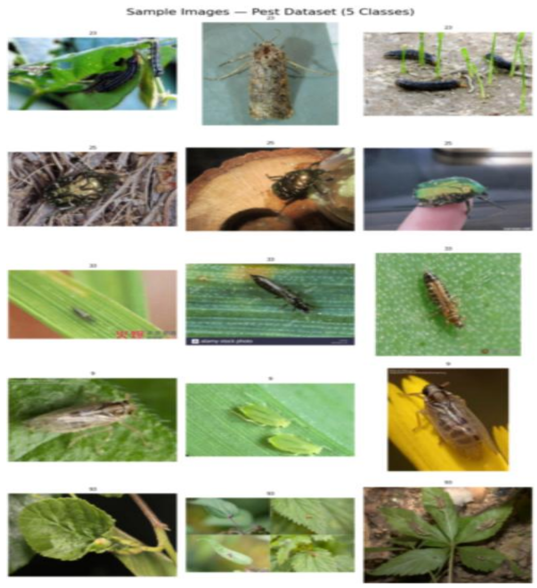

Figure 9: Overview of Machine Learning Techniques and Their Categories

4.2 Model Classification

- **ResNet50**

Figure 10 shows a confusion matrix of ResNet50's performance in classifying five chilli leaf types. Note that all chilli leaf types except one are perfectly classified by the ResNet50 model: 10 correct predictions were made by the model for each of the Chilli_Whitefly, Chilli_Leaf_Curl_Virus, Chilli_Leaf_Spot, and Chilli_healthy leaf types. There were 8 correct predictions by the ResNet50 model for the Chilli_Yellowish leaf type; however, 2 predictions were incorrectly classified as belonging to the Chilli_Leaf_Curl_Virus leaf type. A total of 48 out of 50 predictions were correctly classified by the ResNet50 model, giving a correct classification accuracy of 96%.

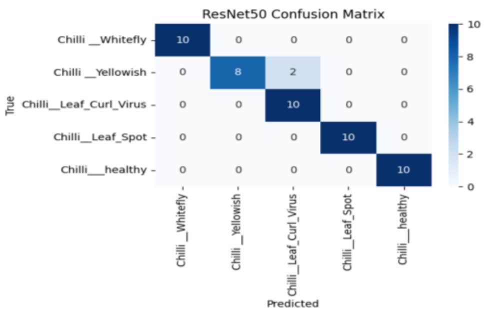

Figure 10: Confusion matrix of ResNet50 with 96% accuracy.

In Figure 11 the training and validation loss patterns are displayed over 10 epochs. The training loss exhibits a sharp decline starting from 0.35 at the beginning until it reaches approximately 0.06 by the fifth epoch. The period from 0.06 to 0.065 marks the stable interval which shows minor fluctuations until the ninth epoch. The validation loss begins at 0.025 and then experiences a slight increase to 0.035 during the first epoch before dropping to approximately 0.01 during the second epoch and achieving its lowest point at 0.005 during the fourth epoch. The system shows stable learning with little overfitting, as indicated by the system's behavior, which reached a final measurement of approximately 0.017.

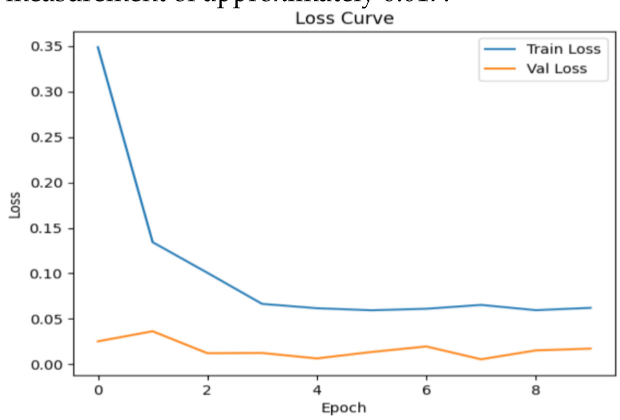

Figure 11: Training and validation loss curves showing steady convergence with minimal overfitting.

In Figure 12, the trend of validation accuracy increases over 10 epochs. The accuracy level is around 0.990 at epoch 0 and then slightly decreases to around 0.978 at epoch 1. It then increases rapidly to around 0.995 by epoch 2 and then stays at a constant level up to epoch 5. It then slightly decreases to almost 0.990 by epoch 6; however, it increases rapidly to around 0.997-0.998 by epochs 7 and 8. It then decreases to around 0.990 by epoch 9.

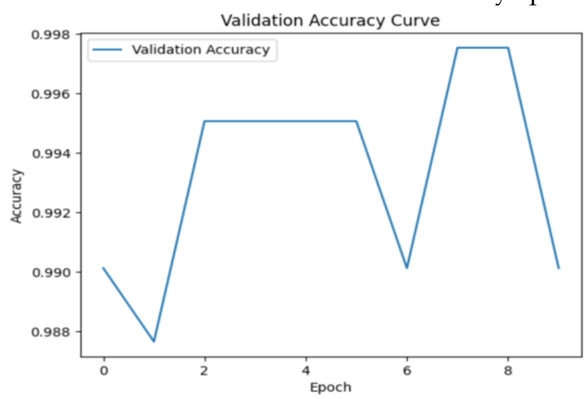

Fig 12: Validation accuracy curve with consistently high performance.

- **EfficientNet-B0**

In Figure 13 the EfficientNet-B0 model's confusion matrix, displays the model's performance across the five classes of chilli leaves; Chilli_Whitefly, Chilli_Leaf_Curl_Virus, Chilli_Leaf_Spot and Chilli_Healthy have all been classified perfectly by having 10 predictions made and 0 incorrect predictions. For Chilli_Yellowish there were 9 predictions made, 1 of which had been incorrectly identified as being Chilli_Leaf_Curl_Virus. There were no other discrepancies in the confusion matrix. Of the 50 samples, 49 samples had been classified correctly, resulting in an accuracy rate of 98%. The performance of the EfficientNet-B0 model is quite impressive; the only slight overlap is between the Chilli_Yellowish and Chilli_Leaf_Curl_Virus classes, which demonstrate a good degree of class separation.

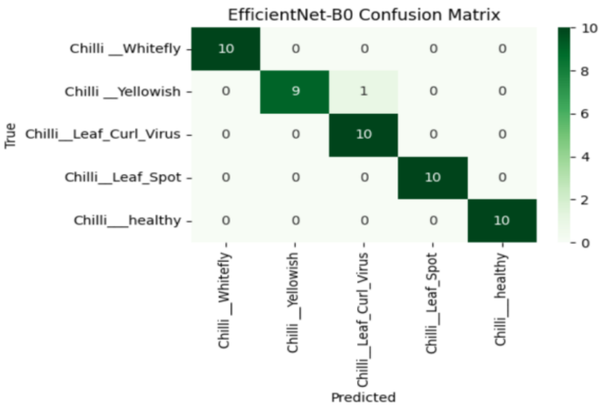

Figure 13: Confusion matrix of EfficientNet-B0 showing 98% accuracy with minimal misclassification.

Figure 14 depicts the training and validation loss patterns of the EfficientNet-B0 model during 10 epochs. The training loss shows a sharp decline starting from approximately 0.76 at epoch 0 which reaches approximately 0.24 at epoch 1 and then continues to decrease until it reaches almost 0.07 at epoch 4. The results from epochs 5 to 9 show validation loss results which maintain a range between 0.05 and 0.06. The validation loss begins at approximately 0.10 and then decreases to approximately 0.05 at the first epoch before reaching its lowest point near 0.02 during the third epoch. The results show minor changes which keep it between 0.01 and 0.03 until it finishes close to 0.025. The two curves show strong convergence which results in only minimal overfitting.

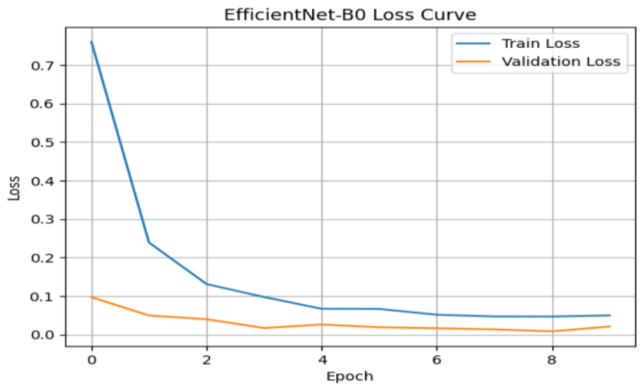

Figure 14: EfficientNet-B0 loss curves showing stable convergence.

Figure 15 illustrates the validation accuracy of the EfficientNet-B0 model over 10 epochs. The accuracy starts at around 0.980 when the model is at epoch 0, and then increases to about 0.988 when the model reaches epoch 1, remaining almost the same in epoch 2. It then increases sharply to about 0.995 in epoch 3. The accuracy decreases slightly to almost 0.993 in epoch 4, and then remains almost the same in epochs 5 and 6, reaching almost 0.995. It then decreases slightly to almost 0.993 in epoch 7, increases sharply to almost 0.995 in epoch 8, and then ends at almost 0.993 in epoch 9.

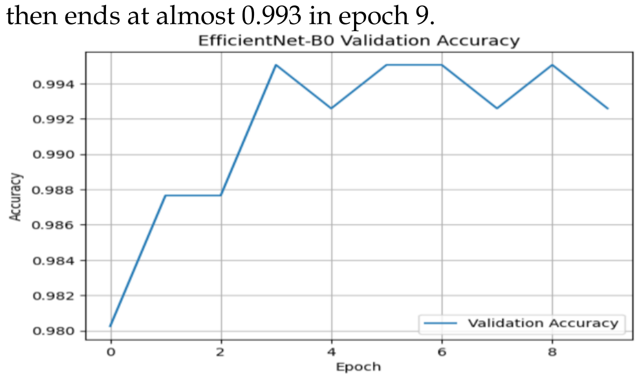

Figure 15: EfficientNet-B0 validation accuracy with stable high performance.

- **AlexNet**

Figure 16 shows the AlexNet model's confusion matrix for 5 different chilli plants' leaves which are Chilli_Whitefly, Chilli_Yellowish, Chilli_Leaf_Spot, & Chilli_healthy were accurately classified 100% of the time (10 of 10 correct predictions). However, Chilli_Leaf_Curl_Virus had 9 correct classifications out of 10 (one misclassification to Chilli_healthy). All other classifications of 49 samples were correctly identified, giving an overall classification rate of 98%. The information suggests that the model is performing at a very high level; there was only a small amount of confusion between Chilli_Leaf_Curl_Virus and Chilli_healthy, which demonstrates that the classes can adequately be discriminated within most categories.

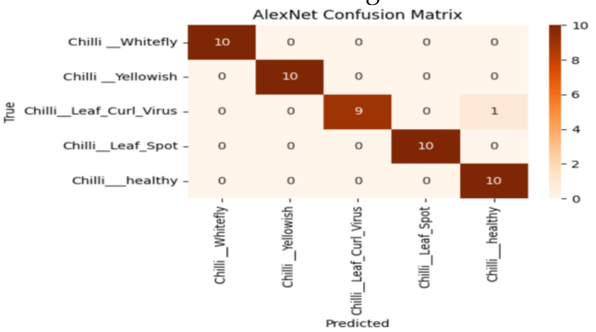

Figure 16: AlexNet confusion matrix showing 98% accuracy with minor misclassification.

Figure 17 shows the trend of training loss and validation loss of the AlexNet model, where the model has been trained for 10 epochs. The loss value decreases sharply at first, reducing from 0.51 to 0.20 in the first epoch, and then continues to decrease gradually to 0.10 after 3 epochs. After that, it fluctuates slightly at 0.07 to 0.10, finally reaching 0.06 at epoch 9. The validation loss starts at 0.09, decreases gradually to 0.02 at epoch 2, and reaches a minimum at 0.01 at epoch 7. After that, some fluctuation is seen, finally reaching 0.02, showing a good convergence with a small amount of overfitting.

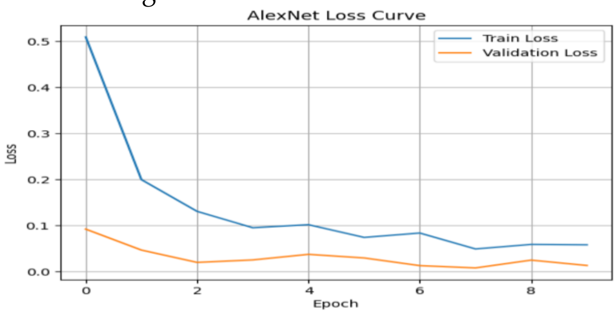

Figure 17: AlexNet loss curves showing stable convergence.

Figure 18 shown the degree to which the AlexNet design achieves accurate results is reflected in the validation performance, over a 10-epoch period. The accuracy begins at approximately 0.968 after the completion of epoch 0 and climbs to around 0.985 by the end of epoch 1. Following this, the accuracy continues to increase to around 0.990 after completing two and three epochs. During epoch 4 there is a slight decrease in the accuracy, falling back to about 0.985; however, the accuracy rises relatively quickly to approximately 0.988 by the end of epoch 5. After attaining an approximate accuracy of 0.995 after completing six epochs, the accuracy climbs to its highest point of nearly 0.997 after completing seven epochs. Over the final two epochs of this evaluation (epochs 8 and 9), the accuracy stabilized around 0.995, indicating that there were consistently high levels of accuracy throughout the entire period of evaluation.

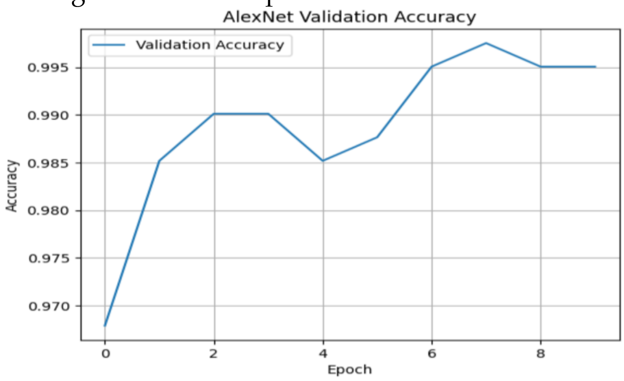

Figure 18: AlexNet validation accuracy showing stable high performance.

4.3 CNN Model Comparison on Chilli Disease Dataset

Figure 19 illustrates the comparison of the test accuracy of the three different CNN models for the chilli disease dataset. ResNet50 has an accuracy of 0.96, which is satisfactory but lower compared to the other two models. EfficientNet-B0 and AlexNet have higher accuracy of 0.98, showing better performance in classification. The difference in accuracy of 2% confirms the efficiency of EfficientNet-B0 and AlexNet in feature extraction compared to ResNet50. All the models have accuracy higher than 95%, showing reliable performance in classification. EfficientNet-B0 and AlexNet have better performance compared to the other models.

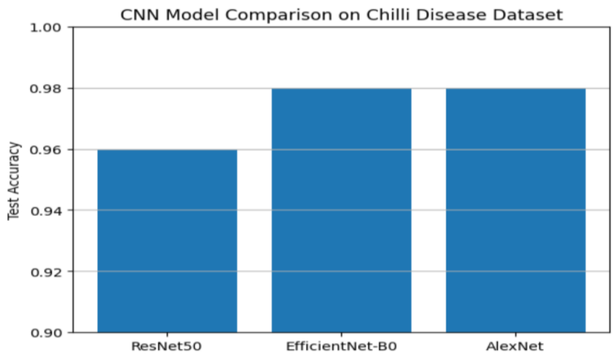

Figure 19: Comparison of CNN models showing EfficientNet-B0 and AlexNet outperform ResNet50.

Figure 20 represented ResNet50, EfficientNet-B0, and AlexNet that have been evaluated for validation accuracy over 10 epochs, The validation accuracy of ResNet50 starts around 0.990, peaks at approximately 0.997 during epochs 7 and 8, then fluctuates slightly around 0.990 by the end of the 10 epochs. The validation accuracy of EfficientNet-B0 starts at approximately 0.980, increases steadily to around 0.995 by epoch three, and has minimal fluctuation to finish around 0.993. The validation accuracy of AlexNet is the lowest starting value at approximately 0.968, but it increases very quickly to approximately 0.990 by epoch two and peaks approximately 0.997 at epoch seven before stabilizing around 0.995. All of these models have high accuracy; therefore, AlexNet and EfficientNet-B0 have consistent levels of high accuracy and comparable performance levels.

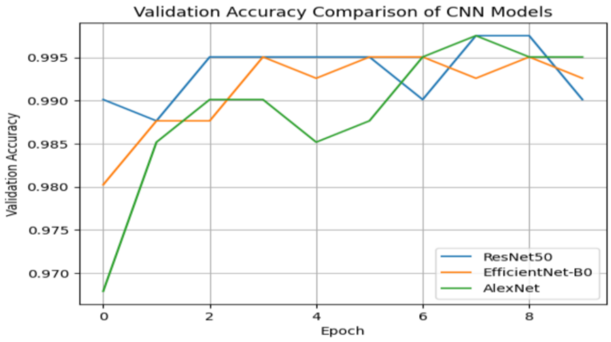

Figure 20: Validation accuracy comparison showing high and stable performance across models.

4.4 YOLOv8 Pest Detection Performance

Figure 21 demonstrates the performance of YOLOv8 in the detection of pests over 20 epochs based on mAP50 and mAP50-95 metrics. mAP50 starts from 0.54, decreases to 0.43 at epoch 2, and then increases steadily to reach 0.71 by epoch 6. It continues to increase to reach 0.83 and 0.84 by epochs 8 and 10, respectively, with a slight decrease to 0.75 by epoch 11. After that, it increases steadily to reach 0.94 by epoch 20. mAP50-95 starts from 0.49, decreases to 0.38, and then increases steadily to reach 0.94 by epoch 20.

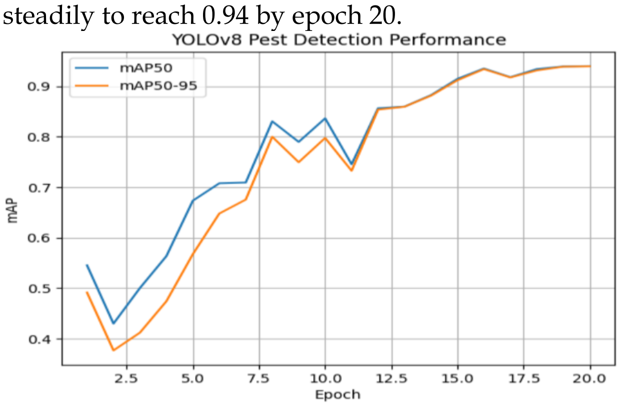

Figure 21: YOLOv8 performance showing steady improvement in mAP metrics.

4.5 Model Performance Comparision

Figure 22 shows the accuracy results from three pest detection models. YOLOv8 achieves the highest accuracy of 0.90 (90%), indicating superior detection performance among the models. AlexNet follows with an accuracy of 0.86 (86%), showing slightly lower but still strong performance. The Hybrid model records the lowest accuracy at 0.85 (85%), closely trailing AlexNet. The best and worst performing models show a 5% performance gap which demonstrates a moderate difference. Overall, all models demonstrate good accuracy above 85%, with YOLOv8 emerging as the most effective model for pest detection in this comparison.

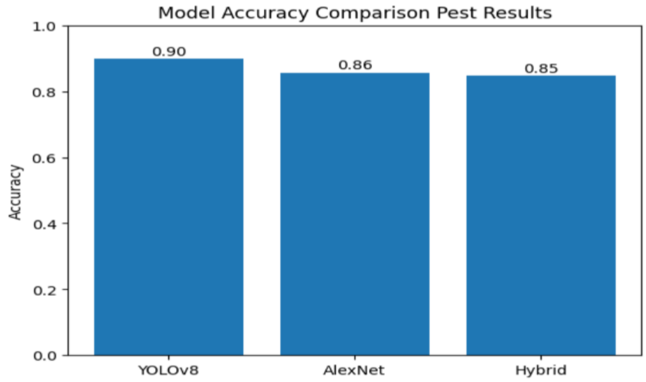

Figure 22: Model accuracy comparison showing YOLOv8 achieves the highest performance.

Figure 23 represents the hybrid model evaluation displays five disease class classification performance metrics. The Healthy class has precision 0.9981 and recall 0.9967 and F1-score 0.9984. The Leaf_Curl_Virus test results show precision 0.9981 and recall 0.9984 and F1-score 0.9962. The Leaf_Spot test results show precision 0.9976 and recall 0.9996 and F1-score 0.9963. The Whitefly classification shows precision 0.9980 and recall 0.9967 and F1-score 0.9964. The Yellowish test results show precision 0.9990 and recall 0.9954 and F1-score 0.9987. The classification performance across all classes maintains excellent standards because all metrics exceed 0.995.

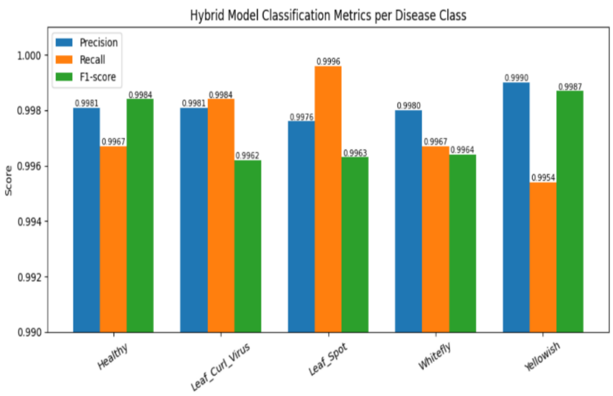

Figure 23: Hybrid model metrics showing high precision, recall, and F1-scores across classes.

5. Conclusion

The research paper identifies the potential of using deep learning methods to combine automated pest detection and disease classification of the chilli crops. The proposed system manages to unite the ResNet50, EfficientNet-B0, and AlexNet classification models with the YOLOv8 detection system to provide precise and real-time performance in the case of working with natural fields. The results indicate that EfficientNet-B0 and AlexNet are better in classifying diseases than other models, whereas YOLOv8 shows consistent localization of a pest despite adverse conditions such as background noise and occlusions. The system will identify high impact pests such as fruit borers and cutworms and help to formulate accurate eradication plans. This will reduce the wastage of pesticides, environmental degradation, and yield of crops. Also, the combination of AI and the availability of technologies such as mobile imaging makes the solution viable to apply in the field. The research is relevant to the development of smart farming as it helps to shift the current situation of reactive, traditional pest control to proactive and information-based decision-making frameworks.

REFERENCES

1. Karim, KM Rezaul, Mohd Y. Rafii, Azizah Binti Misran, Mohd Firdaus Bin Ismail, Abdul Rahim Harun, Md Mahmudul Hasan Khan, and Mst Farhana Nazneen Chowdhury. "Current and prospective strategies in the varietal improvement of chilli (Capsicum annuum L.) specially heterosis breeding." *Agronomy* 11, no. 11 (2021): 2217.
2. Barboza, Gloria E., Carolina Carrizo García, Luciano de Bem Bianchetti, María V. Romero, and Marisel Scaldaferro. " Monograph of wild and cultivated chili peppers (Capsicum L., Solanaceae)." *PhytoKeys* 200 (2022): 1.
3. Gowda, Noothan R., and L. T. Nikita. "Insect Pests of Vegetable and Fruit Crops." Advances in Applied Entomology (2025): 52.
4. Skendžić, Sandra, Monika Zovko, Ivana Pajač Živković, Vinko Lešić, and Darija Lemić. "The impact of climate change on agricultural insect pests." *Insects* 12, no. 5 (2021): 440.
5. Singh, Manjeet, Aseem Vermaa, and Vijay Kumar. "Geospatial technologies for the management of pest and disease in crops." In *Precision Agriculture*, pp. 37-54. Academic Press, 2023.
6. Shoaib, Muhammad, Abolghasem Sadeghi-Niaraki, Farman Ali, Irfan Hussain, and Shah Khalid. "Leveraging deep learning for plant disease and pest detection: a comprehensive review and future directions." *Frontiers in Plant Science* 16 (2025): 1538163.
7. Ali, Sajjad, Muhammad Irfan Ullah, Asif Sajjad, Qaiser Shakeel, and Azhar Hussain. "Environmental and health effects of pesticide residues." In *Sustainable agriculture reviews 48: Pesticide occurrence, analysis and remediation vol. 2 analysis*, pp. 311-336. Cham: Springer International Publishing, 2020.
8. Adetunji, Charles Oluwaseun, Olugbemi T. Olaniyan, Osikemekha Anthony Anani, Abel Inobeme, Osarenkhoe O. Osemwegie, Daniel Hefft, and Olalekan Akinbo. "Artificial intelligence and automation for precision pest management." In *Sensing and Artificial Intelligence Solutions for Food Manufacturing*, pp. 49-70. CRC Press, 2023.
9. Vidya Madhuri, E., J. S. Rupali, S. P. Sharan, N. Sai Pooja, G. S. Sujatha, Dhananjaya P. Singh, Khurshid Ahmad, Amrender Kumar, and Ratna Prabha. "Transforming pest management with artificial intelligence technologies: The future of crop protection." *Journal of Crop Health* 77, no. 2 (2025): 48.
10. Tirkey, Divyanshu, Kshitiz Kumar Singh, and Shrivishal Tripathi. "Performance analysis of AI-based solutions for crop disease identification, detection, and classification." *Smart Agricultural Technology* 5 (2023): 100238.
11. Tabassum, Husna, and Prasannavenkatesan Theerthagiri. "Performance Analysis of AI-based Learning Models on Leaf Disease Prediction." In *2022 4th International Conference on Circuits, Control, Communication and Computing (I4C)*, pp. 85-88. IEEE, 2022.
12. Keivani, Mohammad, Jalil Mazloum, Ezatollah Sedaghatfar, and Mohammad Bagher Tavakoli. "Automated analysis of leaf shape, texture, and color features for plant classification." *TRAITEMENT du Signal* 37, no. 1 (2020): 17-28.
13. Shafik, Wasswa, Ali Tufail, Liyanage Chandratilak De Silva, Rosyzie Anna Awg Haji Mohd Apong, and Ki-Hyung Kim. "Deep learning technique for plant disease classification and pest detection and model

explainability elevating agricultural sustainability." *BMC Plant Biology* 25, no. 1 (2025): 1491.
14. SS, Vinod Chandra, Anand Hareendran, and Ghassan Faisal Albaaji. "Precision farming for sustainability: An agricultural intelligence model." *Computers and Electronics in Agriculture* 226 (2024): 109386.
15. Shoaib, Muhammad, Abolghasem Sadeghi-Niaraki, Farman Ali, Irfan Hussain, and Shah Khalid. "Leveraging deep learning for plant disease and pest detection: a comprehensive review and future directions." *Frontiers in Plant Science* 16 (2025): 1538163.
16. Jayasuriya, Kalana, Dilusha Kotapolage, Shalitha Gamage, Prasanna Haddela, and Nadeesa Pemadasa. "Plant Stresses and Pest Attack Detection Using Convolutional Neural Networks with Advance Preprocessing Techniques in Chili Plants." In *Proceedings of the Future Technologies Conference*, pp. 17-33. Cham: Springer International Publishing, 2021.
17. Dalal, Mukesh, and Payal Mittal. "A Systematic Review of Deep Learning-Based Object Detection in Agriculture: Methods, Challenges, and Future Directions." *Computers, Materials & Continua* 84, no. 1 (2025).
18. Aziz, Danishta, Summira Rafiq, Pawan Saini, Ishtiyaq Ahad, Basanagouda Gonal, Sheikh Aafreen Rehman, Shafiya Rashid et al. "Remote sensing and artificial intelligence: revolutionizing pest management in agriculture." *Frontiers in Sustainable Food Systems* 9 (2025): 1551460.
19. Sharma, Kushagra, and Shiv Kumar Shivandu. "Integrating artificial intelligence and Internet of Things (IoT) for enhanced crop monitoring and management in precision agriculture." *Sensors International* 5 (2024): 100292.
20. Thomas, Jaya Christa Sargunar, Suhidhana Manikandarajan, and Tinaga Kamalakkannan Subha. "AI based pest detection and alert system for farmers using IoT." In *E3S web of conferences*, vol. 387, p. 05003. EDP Sciences, 2023.
21. Rustia, Dan Jeric Arcega, Lin-Ya Chiu, Chen-Yi Lu, Ya-Fang Wu, Sheng-Kuan Chen, Jui-Yung Chung, Ju-Chun Hsu, and Ta-Te Lin. "Towards intelligent and integrated pest management through an AIoT-based monitoring system." *Pest Management Science* 78, no. 10 (2022): 4288-4302.
22. Nilam, AA H., J. S. Perera, IS G. Warnakulasuriya, N. W. Edirisooriya, J. K. Joseph, and D. M. G. T. Dassanayake. "Mobile Application for Chili Disease Detection, Correction, Prevention and Price Prediction." In *2023 5th International Conference on Advancements in Computing (ICAC)*, pp. 621-626. IEEE, 2023.
23. Kumara, Rajeev. "ASSESSING THE IMPACT OF DEEP LEARNING ON PROACTIVE PEST AND DISEASE MANAGEMENT FOR SUSTAINABLE AGRICULTURAL PRODUCTION OPTIMIZATION." *International Journal of Applied Mathematics* 38, no. 11s (2025): 1436-1458.
24. Li, Chunhua, and Meihong Wang. "Pest and disease management in agricultural production with artificial intelligence: Innovative applications and development trends." *Advances in Resources Research* 4, no. 3 (2024): 381-401.
25. Leite, Douglas Vieira, Alisson Vasconcelos de Brito, Gregorio Guirada Faccioli, and Gustavo Haddad Souza Vieira. "Deep Learning Models for Detection and Severity Assessment of Cercospora Leaf Spot (Cercospora capsici) in Chili Peppers Under Natural Conditions." *Plants* 14, no. 13 (2025): 2011.
26. Odounfa, Mireille Gloria Founmilayo, Castro Gbêmêmali Hounmenou, Valère Kolawolé Salako, Antoine Affokpon, and Romain L. Glèlè Kakaï. "Deep learning enables precision agriculture for sustainable chili pepper disease detection in Benin." *Discover Artificial Intelligence* 5, no. 1 (2025): 315.
27. Hamim, Sultanul Arifeen, and Akinul Islam Jony. "Enhanced deep learning model architecture for plant disease detection in Chilli plants." *Journal of Edge Computing* 3, no. 2 (2024): 136-146.
28. Kanaparthi, Kantha Raju, and S. Sudhakar Ilango. "Deep Learning Methods for Detecting Chilli Pests–A Novel Performance Analysis." *Ecological Engineering & Environmental Technology* 25 (2024).
29. Agustian, Indra, Ruvita Faurina, Sahrial Ihsani Ishak, Ferzha Putra Utama, Kusmea Dinata, and Novalio Daratha. "Deep learning pest detection on Indonesian red chili pepper plant based on fine-tuned YOLOv5." *International Journal of Advances in Intelligent Informatics* 9, no. 3 (2023): 383-401.
30. Chakrabarty, Sourav, Pathour Rajendra Shashank, Chandan Kumar Deb, Md Ashraful Haque, Pradyuman Thakur, Deeba Kamil, Sudeep Marwaha, and Mukesh Kumar Dhillon. "Deep learning-based accurate detection of insects and damage in cruciferous crops using YOLOv5." *Smart Agricultural Technology* 9 (2024): 100663.
31. Jia, Shuyi, Maryam Horri Rezaei, and Barmak Honarvar Shakibaei Asli. "Enhancing Pest Detection in

Deep Learning Through a Systematic Image Quality Assessment and Preprocessing Framework." *Journal of Experimental and Theoretical Analyses* 3, no. 4 (2025): 39.

32. Nurokhman, Akhmad, Sarif Surorejo, Rifki Dwi Kurniawan, and Gunawan Gunawan. "Application of computer vision techniques to detect diseases and pests of chili plants." *Journal of Intelligent Decision Support System (IDSS)* 7, no. 1 (2024): 10-18.
33. Balasubramaniam, S., Sandra Grace Nelson, M. Arishma, Anjali S. Rajan, and Kumar K. Satheesh. "Machine learning based disease and pest detection in agricultural crops." *EAI Endorsed Transactions on Internet of Things* 10 (2023).
34. Islam, Nahina, Md Mamunur Rashid, Santoso Wibowo, Cheng-Yuan Xu, Ahsan Morshed, Saleh A. Wasimi, Steven Moore, and Sk Mostafizur Rahman. "Early weed detection using image processing and machine learning techniques in an Australian chilli farm." *Agriculture* 11, no. 5 (2021): 387.
35. Wang, Xuewei, Jun Liu, and Qian Chen. "An advanced deep learning method for pepper diseases and pests detection." *Plant Methods* 21, no. 1 (2025): 70.
36. https://www.kaggle.com/datasets/ahmadalmahsiri/chili-plant-disease
37. https://www.kaggle.com/datasets/rtlmhjbn/ip02-dataset
38. Wen, Long, Xinyu Li, and Liang Gao. "A transfer convolutional neural network for fault diagnosis based on ResNet-50." *Neural Computing and Applications* 32, no. 10 (2020): 6111-6124.
39. Hochreiter, Sepp. "The vanishing gradient problem during learning recurrent neural nets and problem solutions." *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems* 6, no. 02 (1998): 107-116.
40. Mukti, Ishrat Zahan, and Dipayan Biswas. "Transfer learning based plant diseases detection using ResNet50." In *2019 4th International conference on electrical information and communication technology (EICT)*, pp. 1-6. IEEE, 2019.
41. Krismawan, Andi Danang. "Tomato leaf diseases classification using convolutional neural networks with transfer learning Resnet-50." *Kinetik: Game Technology, Information System, Computer Network, Computing, Electronics, and Control* (2024): 149-158.
42. Kanimozhi, T., V. Rajeswari, R. Suguna, J. Nirmaladevi, P. Prema, B. Janani, and R. Gomathi. "RWHO: A hybrid of CNN architecture and optimization algorithm to predict basal cell carcinoma skin cancer in dermoscopic images." The Scientific Temper 15, no. 02 (2024): 2138-2142.
43. Abd El-Ghany, Sameh, Mahmood A. Mahmood, and A. A. Abd El-Aziz. "Adaptive Dynamic Learning Rate Optimization Technique for Colorectal Cancer Diagnosis Based on Histopathological Image Using EfficientNet-B0 Deep Learning Model." *Electronics* 13, no. 16 (2024): 3126.
44. Salka, Tanko Daniel, Marsyita Binti Hanafi, Sharifah M. Syed Ahmad Abdul Rahman, Dzarifah Binti Mohamed Zulperi, and Zaid Omar. "Plant leaf disease detection and classification using convolution neural networks model: a review." *Artificial Intelligence Review* 58, no. 10 (2025): 322.
45. Rozlan, Suhana, and Marsyita Hanafi. "Efficacy of chili plant diseases classification using deep learning: a preliminary study." *Comput Sci* 25 (2022): 1442-1449.
46. Riza, Jaohar, Sadia Ridita Shohag Barman, Zaeed Mahmud, and Aditi Bhattacharya. "PhytoCare: A hybrid approach for identifying Rice, Potato and Corn diseases." PhD diss., PhD thesis, University of Liberal Arts Bangladesh, 02 2024, 2023.
47. 53.Zhong, Jiaqi, Huaming Qian, Huilin Wang, Wenna Wang, and Yipeng Zhou. "Improved real-time object detection method based on YOLOv8: a refined approach." *Journal of Real-Time Image Processing* 22, no. 1 (2025): 4.