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TOPICAL REVIEW

State-of-the-Art Deep Learning Algorithms for Internet of Things-Based Detection of Crop Pests and Diseases: A Comprehensive Review

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ABSTRACT Plant pest and disease management, especially in the early stages of infestation, is a critical challenge that poses significant threats and has potential to devastate agricultural crops, causing total yield loss and food insecurity. Traditional inspection methods are time-consuming and prone to errors due to limited labor expertise. Therefore, to tackle these challenges, harnessing advanced technologies such as artificial intelligence (AI), Machine Learning/Deep Learning (ML/DL), and Internet of Things (IoT) is essential for managing and mitigating agriculture hazards. This research presents a comprehensive review of the state-of-the-art DL architectures integrated with IoT-based systems applied to plant pest and disease detection (PPDD) by investigating different potential approaches that have been employed using DL and IoT up to the year 2024 to address challenges in agriculture. Convolutional Neural Network (CNN) architectures for image recognition, object detection, and their integration with IoT, embedded into mobile devices and unmanned aerial vehicles (UAV) are explored. Moreover, the research discusses the advantages and limitations of these techniques, emphasizing their architecture design, efficiency and accuracy. The findings demonstrate that there is a tradeoff between robustness and complexity among existing techniques, and authors recommend future trends aimed at creating robust models with fewer parameters that are more accurate and easily implementable on small IoT-based and portable devices suitable for in-field and real-time applications. Furthermore, while existing review papers discuss either DL or IoT separately, this research paper uniquely focuses on their combined models, providing a comprehensive overview of the synergistic potential of leveraging IoT-driven technologies alongside advanced DL algorithms to ease the task of researchers in the field of precision agriculture particularly in PPDD.

INDEX TERMS Deep learning, machine learning, crop pest detection, crop disease detection, convolutional neural networks, Internet of Things.

I. INTRODUCTION

Agricultural products are crucial for human existence, and people have been striving to increase their productivity. For instance, corn is the human staple food that sustains millions of people across the globe, serves as feed for livestock, and recently has started being used for fuel production and other industrial applications [1], [2]. However, a myriad of invasive pests and diseases pose threats to productivity and quality of crop yields, leading to substantial crop losses and economic hardship for farmers [3], [4]. The Food and Agriculture Organization (FAO) estimates that 20% to 40 % of world crop production is lost due to pests and diseases [5]. Several factors often related to a combination of environmental, biological, and agronomic conditions contribute to presence and proliferation of the plant pests and diseases. These factors include climate conditions, migratory pests and other animals, cultural practices, human activities, weeds hosts, and pathogens. Pathogens can exacerbate the plant growth conditions when they are not properly managed [6].

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Farmers use pesticides and insecticides as a keystone of modern agriculture to fight against pests and diseases, playing an essential role in increasing crop yields and ensuring food security. Nevertheless, these chemical agents designed to manage and control pests, pose substantial health risks for humans and negative environmental impact as well as implications for long-term sustainability [7], [8]. For instance, poisoning from pesticides is responsible for nearly 300 thousand deaths worldwide every year [9] and a total estimated environmental and social loss of 10 billion USD per year due to pesticide application [10]. Detecting and identifying pests and diseases at their early stages of development is a proactive approach to mitigate the damage before they escalate. The ultimate goal is to reduce reliance on pesticides and adopt integrated pest management (IPM) strategies for pest and disease control [11].

Traditional methods of preventative measures for early pest and disease control in agricultural crops have been adopted for enhancing yield production [12]. These traditional approaches involve human inspection to detect the presence of visible pests on plant and visible symptoms on leaves, such as necrosis, discoloration, spots, or any signs of stunted growth or wilting. However, these approaches are expensive, time consuming, labor-intensive, and inaccurate, as they are prone to human mistakes or biased decisions due to lack of expertise [5]. Furthermore, traditional methods are subjected to overuse of fertilizers, insecticides, and pesticides, resulting in premature or delayed treatment of infected plants. The limitations of these traditional approaches have motivated researchers to propose technological solutions for precision agriculture [13], [14].

The breakthrough of Artificial Intelligence (AI) technology triggered the application of computer vision techniques in agriculture to precisely classify and locate pests and diseases in plants [15], [16]. Machine Learning (ML) conceived by Arthur Samuel in 1952 has gradually gained momentum within the research community over the past few decades. Common traditional ML techniques such as Support Vector Machine (SVM), Logistic Regression (LR), Random Forest (RF), K-Nearest Neighbors (KNN), Linear Discriminant Analysis (LDA), and Naïve Bayes (NB) have been useful in classifying Pests and diseases [17], [18], [19].

Nevertheless, these traditional ML techniques rely on manual feature engineering for the model training which is time-consuming, prone to limited scalability, generalization issues, and overfitting. Hence, studies over the last few decades have started incorporating automatic feature extraction to enhance accuracy by exploring advanced image processing techniques, including the use of Artificial Neural Networks (ANN) [20].

Deep learning (DL) techniques, as a remedy for the limitations of traditional ML techniques, have revolutionized image processing by offering a dynamic and adaptable approach for visual data interpretation [21], [22], [23]. In the context of agriculture, DL based on Convolutional Neural Networks (CNNs) has emerged as a particularly powerful tool, enabling automatic identification, classification and localization of pests and diseases on real-time [24], [25]. This approach also reduces the computational cost compared to traditional ANN. Several DL architectures have been developed and proven effective in recognizing and localizing pests and diseases within images. These DL/CNN architectures include AlexNet, GoogLeNet, VGGNet, ResNet, MobileNet, DenseNet, and EfficientNet [26]. Additionally, other DL architectures such as R-CNN, Fast R-CNN, Faster R-CNN, SSD, EfficientDet, and YOLO are used to identify and precisely locate pests within images or video frames [27], [28], [29].

Specialized sensors and imaging technologies have been instrumental in capturing visual data in modern agriculture. These sophisticated camera sensor technologies are intricately associated with DL techniques for successful detection of plant pests and diseases. High-resolution RGB cameras have been extensively employed, providing detailed visual information about the crop [30]. Furthermore, hyperspectral and multispectral imaging techniques have been widely used for capturing data across multiple spectral bands to detect subtle variations indicative of plant stress, disease, or pest infestations. Additionally, thermal and infrared cameras have been utilized to detect temperature variations associated with presence of pest and disease infestation [31]. The development of new sensing technologies, such as Light Detection and Ranging (LiDAR), has opened new opportunities for three-dimensional crop mapping, offering a comprehensive analysis of pest and disease infestation [32]. Moving platforms such as UAVs [33], robots, and satellites carrying these sensors have further improved data collection efficiency, by enabling coverage of large agricultural fields [34].

The adoption of Internet of Things (IoT) technology has emerged as a pivotal force in revolutionizing pest and disease identification in agriculture, especially when combined with advanced image processing and DL algorithms [35] [36]. Application of IoT-enabled devices, such as cameras on unmanned aerial vehicles (UAVs), robotic systems, and mobile platforms enables real-time data collection from farm fields [37], [38]. These devices capture high resolution images, which, when coupled with DL techniques, allow automatic recognition of pests and diseases with high accuracy. The continuous transmission of image data through IoT networks to centralized systems amplifies the scalability and effectiveness of the identification process [39]. Furthermore, integrating environmental sensors within these IoT systems, offers valuable contextual information, contributing to the understanding of factors affecting crop health [39]. Therefore, the combination of IoT, image analysis, and DL not only simplifies the identification process but also equips farmers with timely insights, enabling them to make informed decisions to minimize the impact of pests and diseases on crop production [40]. This combination of technologies improves significantly the advancement in precision agriculture, ensuring sustainable and data-centric strategies for pest and disease control at the early stage of infestation.

While the existing review papers typically focus on either DL or IoT separately and their general applications in agriculture [41], [42], this review paper provides a comprehensive overview of the integration of IoT and DL technologies for precision agriculture, with a specific focus on pest and disease detection in crops. By synthesizing existing research and real-world applications, this study highlights the synergetic potential of combining IoT-driven data collection with advanced DL technology. It offers detailed analysis of advanced DL models embedded in IoT devices and their performance in agricultural contexts, specifically for crop pest and disease management [43].

Ultimately, this review contributes to the advancement of knowledge in precision agriculture by highlighting emerging trends, challenges, and opportunities at the intersection of IoT and DL with significant implications for sustainable crop production and food security. Additionally, it provides the clear understanding of the state-of-the-art in DL and IoT integration for pest and disease management, serving as a valuable resource for potential researchers in the field.

The remaining sections of this review paper are organized as follow: Section II depicts the research methods used to search, select, and analyze the state-of-the-art studies related to plant pest and disease detection. Section III investigates CNN architectures and their integration with IoT for plant pest and disease detection. Section IV presents Key findings while Section V concludes the review paper and highlights recommendations and opportunities for future works for early identification of pests and diseases threatening different crops.

II. RESEARCH METHOD

This section describes the process of selecting and analyzing research papers considered for this review. The research procedure was performed based on the following steps:

1. Research articles published up to 2024 were selected from well-known academic research journals and databases such as IEEE Access, Science Direct, PubMed, Web of Sciences, springer, Elsevier, IEEE Xplore, Directory of Open Access Journals, EBSCO and JSTOR.
2. The research was based on the following criteria:
    i. DL/CNN architectures-based image recognition for plant pest and disease detection.
    ii. DL/CNN architectures-based object detection for plant pest and disease detection.
    iii. Integration of IoT and DL algorithms for plant pest and disease detection.
3. Selected articles were analyzed based on their CNN-based image recognition architectures, CNN-based object detection architectures, and IoT integrated with CNN techniques applied in Pest and disease detection. The analysis also focused on results obtained based on their performance metrics. The flowchart presented in Figure1, indicates the flow of the review paper development.

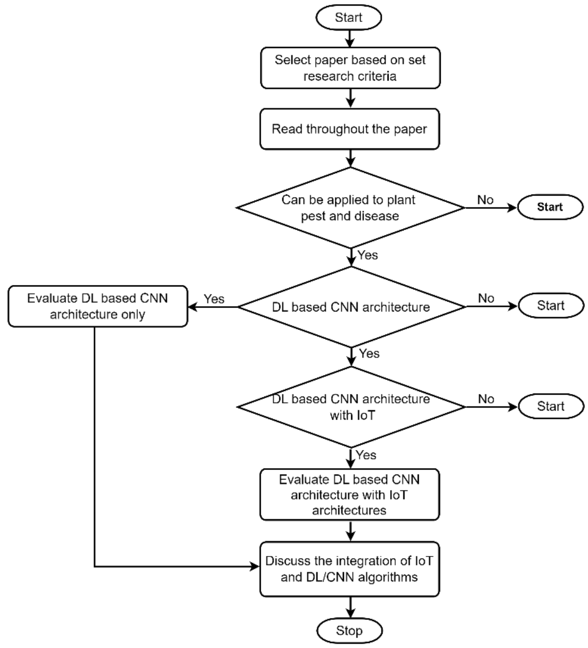


FIGURE 1. **The flowchart of research method.**

Performance Metrics for CNN: The model performance assessment and quantification is essential practice in the domain of CNN-based image recognition and object detection to evaluate the effectiveness of the model [44]. The standard classification performance metrics including accuracy, precision, recall, F_1-score, Mean Average Precision, Intersection Over Union (IoU) and Area Under the ROC Curve (ROC-AUC) provide insights into the strengths and limitations of CNN architectures, enabling thorough comparisons of CNN algorithms [45]. These key performance metrics, when applied to image recognition and object detection tasks for pest and disease detection, offer a comprehensive evaluation of model performance. They ensure accurate identification of affected areas while minimizing false positives and false negatives, crucial for effective pest and disease management.

Accuracy of the model measures the overall correctness of predictions by providing an immediate insight into the model's performance

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

where:

- TP (True Positive): instances the model correctly predicts as positive class
- TN (True Negative): Instances the model correctly predicts as negative class
- FP (False Positive): Instances the model incorrectly predicts as positive class
- FN (False Negative): Instances the model incorrectly predicts as negative class

Precision shows the ratio of correctly predicted positive observations compared to the total predicted positive observations. Specifically for pest and disease detection, a high precision demonstrates the model's adeptness in identifying pest or disease-infected areas within images while minimizing false positives.

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

Recall measures the ratio of correctly predicted positive observations to all observations in the actual positive class, ensuring all positive instances are captured. Particularly for pest and disease, recall determine the model's ability to correctly identify all instances of pest or disease within the images compared to the total actual instances of pest or disease.

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

F_1-score metric determines balance between recall and precision, indicating a model's ability to achieve both high precision and high recall concurrently. For pest and disease detection model, F_1-score provides a balanced assessment of a model's performance for detecting infested crop area within an image.

$$F_1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{4}$$

The Mean Average Precision (mAP) is the weighted mean of precisions at each threshold of Intersection over Union (IoU), averaged across all classes. The weight represents the increase in recall from the previous threshold. Alternatively, it can be defined as the ratio of the area under the precision-recall curve, obtained by varying the IoU threshold, to the number of IoU threshold variations, and then averaged across all classes.

The average precision (AP) can be computed as:

$$AP = \frac{\sum_{i=1}^{N} (P_i + P_{i+1})\Delta R_i}{2N} \tag{5}$$

where N is the number of threshold increments, P_i is the precision at i^{th} IoU threshold, and ΔR_i is the increase in recall from i^{th} to $(i+1)^{th}$ IoU threshold.

The mean average precision is given by:

$$mAP = \frac{\sum_{k=1}^{k=Q} AP_k}{Q} \tag{6}$$

where Q is the number of classes.

In the context of pest and disease detection, mAP offers a consolidated evaluation of the model's ability to accurately identify various pest/disease-infected areas within images while effectively balancing between precision and recall.

For plant pest and disease detection, a model that achieves a high accuracy maybe considered the best. When models have same accuracy, prioritizing higher recall over precision may be beneficial. Such a model can guarantee a high percentage of all cases of plant pests and disease are detected, which is very important for comprehensive pest and disease management. However, this approach may incur costs due to false positives, which aren't accounted for by the metric. Conversely, a model with high precision minimizes false positives but doesn't guarantee maximal detection of positive cases. The F_1-score and mAP stand out as optimal choices for selecting among models of same accuracy. They both aim to provide a measure that balances between recall and precision, thus optimizing resource allocation. However, while F1-score offers a general measure, mAP provides a comprehensive accuracy measure tailored for object detection models, incorporating the precision of bounding boxes.

III. INVESTIGATING CNN ALGORITHMS AND THEIR INTEGRATION WITH IoT FOR PLANT PEST AND DISEASE DETECTION

Various research have been conducted in precision agriculture [46], employing advanced DL techniques in image recognition and object detection to automatically identify and categorize pests and diseases affecting different crops [47]. The state-of-the-art is marked by a convergence of cutting-edge Convolutional Neural Network (CNN) architectures and each contributed uniquely to the precision and efficiency of detection [48]. In addition, the integration of IoT technology with DL algorithms has advanced the precision agriculture and attracted attention of many researchers. This section discusses the state-of-the-art CNN algorithms based on image recognition and object detection approaches and integration of IoT and DL technologies in agricultural crop pests and diseases detection [49].

A. DL/CNN-BASED IMAGE RECOGNITION ARCHITECTURES FOR PLANT PEST AND DISEASE DETECTION

The generic CNN architecture for pest image classification is depicted in Fig. 2. The input layer represents the raw input plant image fed into the DL/CNN model and it is converted to a predetermined size and format suitable for further processing in convolution layers. The convolution layers which are the core building blocks of the CNN architecture, applies filters or kernels to the input plant image for feature extraction such as shapes, edges, and colors. The convolution results are then summed up and passed to activation function like ReLU for non-linearity determination, generating a number of feature maps. Next, pooling layers, like max pooling downsample the generated feature maps to reduce their dimensions. Finally, the extracted features are then flattened into a one-dimensional vector and passed into fully connected layers, which are typically artificial neural network layers that produce output classes of plant pests, diseases or healthy plants.

1) ALEXNET

Ground-breaking model like AlexNet was introduced in 2012 by Krizhevsky et al [50] and deepened the LeNet architecture with 5 convolutional layers, some of which followed

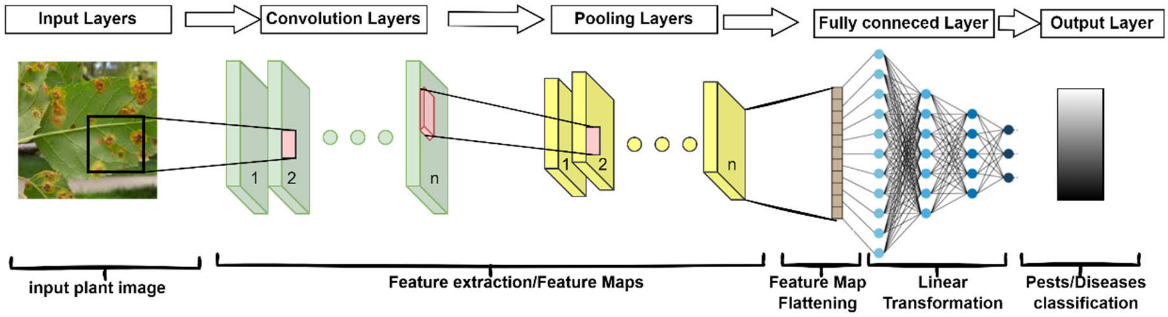


FIGURE 2. Overall architecture of image recognition for plant pest and disease detection.

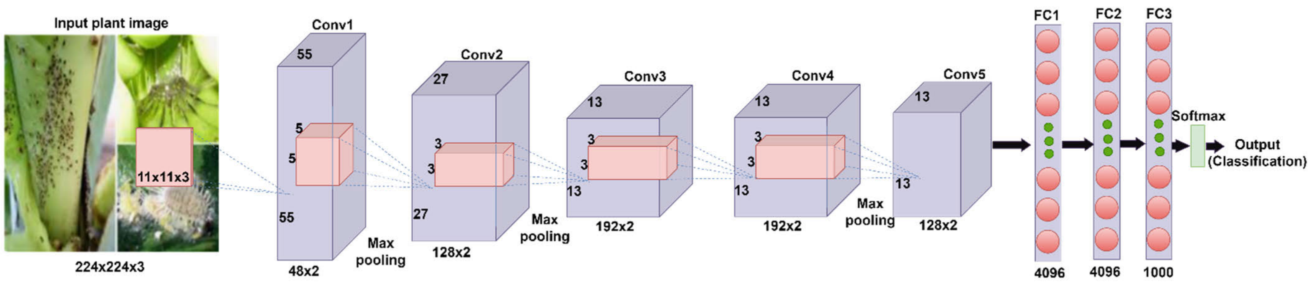


FIGURE 3. Generic architecture of AlexNet [50].

by max-pooling layers, 3 fully connected layers, dropout for overfitting suppression, ReLu activation function in hidden layers, and a Softmax activation function in the output layer as illustrated in the *Fig.3* below.

Various studies have employed CNN algorithms based on AlexNet architecture in the domain of precision agriculture for detecting and managing pests and diseases affecting crops. Lv et al. in [51] developed DMS-Robust AlexNet capable of recognizing and classifying six Maize leaf diseases with 98.62% accuracy. The TCI-ALEXN that improves the original AlexNet architecture by adding a new convolutional layer and new Inception module to enhance the ability of AlexNet features extraction was proposed in [52] and achieved 93.28% accuracy. Sanderson et al. [53] designed a system based on AlexNet architecture and Android platform for detecting tomato leaf diseases with accuracy of 98%. Furthermore, Syarief and Setiawan [54] used AlexNet for features extraction and obtained 93.5% accuracy, while Wu et al. [55] achieved 98.33% accuracy using two-channel CNN. However, while AlexNet architecture has achieved remarkable results, it suffers from overfitting problems and high computational resource demands.

2) GOOGLENET/INCEPTION

To overcome the challenges of scalability, computational complexity, and capturing multi-scale features, the GoogLeNet/Inception was introduced by Szegedy et al. [56]. This achitecture is characterized by inception modules employing parallel pathways of convolutions to efficiently capture multi-scale features, effectively balancing depth and computational efficiency for complex visual recognition tasks as illustrated in Fig.4.a and Fig.4.b [57].

For pest and disease detection, Hu et al. [57] developed and fine-tuned a pre-trained GoogLeNet/Inception model and identified corn leaf disease with 98.05% accuracy. In the study conducted by Li et al. [58], ten different types of pests were classifies using VGG-16, VGG-19, ResNet50, ResNet152, and GoogLeNet based algorithms and GoogLeNet outperformed others with 96.67% accuracy. The study in [59], a model based on the inception layer and residual connection was proposed. This model used depth-wise separable convolution to reduce the number of parameters. When trained on Plant Village for rice disease, the results exhibited 99.66% accuracy. Furthermore, Mohanty et al. [60], Zhang etal. [61] and Souza et al. [62] employed GoogLeNet/Inception models to detect and classify common rice and maize diseases and reached to 99.34%, 98.9%, and 97% accuracy, respectively. Nevertheless, the GoogLeNet/Inception based models are complex in design due to intricate inception modules and they require high computational resources.

3) VGGNET

A deeper CNN architecture known as VGGNet was introduced by Simonyan and Zisserman [63] in 2014. It typically consists of 16 or 19 layers and 3×3 convolutional filters stacked on top of each other, which made the network deeper

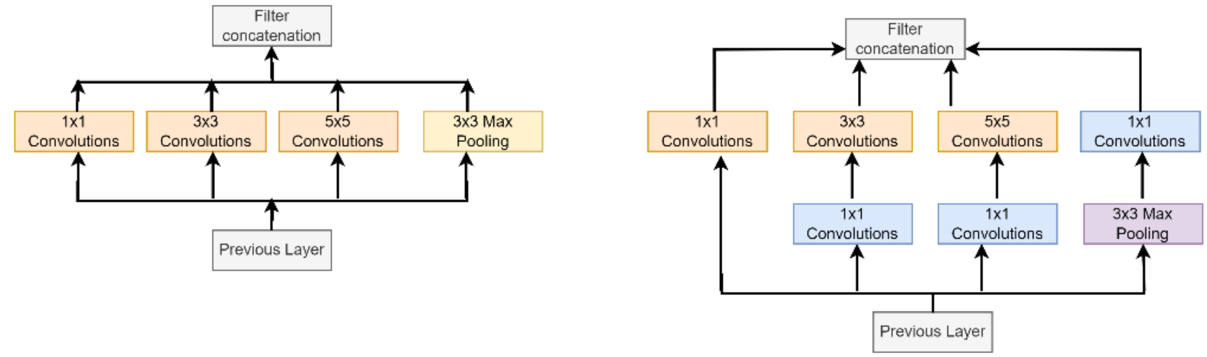


FIGURE 4. (a) Inception module for Naive version, (b) Inception module with dimensionality reduction.

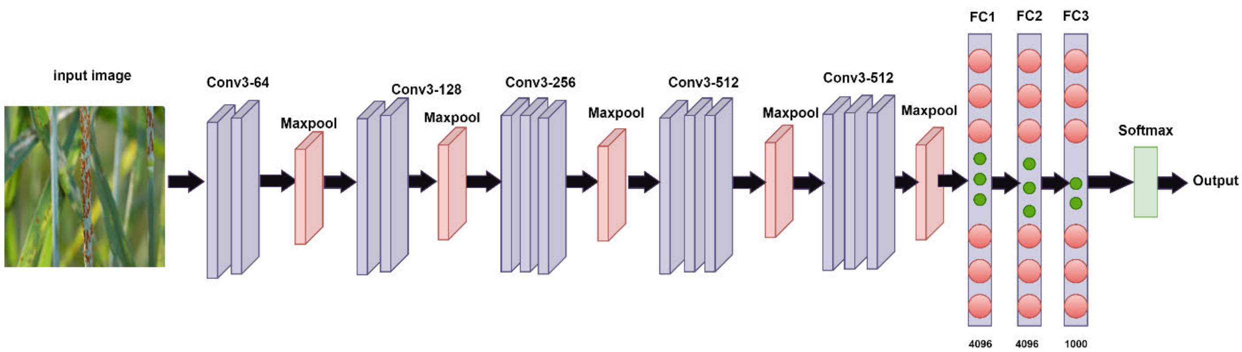


FIGURE 5. Generic architecture of VGGNe [63].

but with improved the performance of image recognition tasks, as depicted in Fig. 5.

Two commonly known VGGNet architectures are VGGNet-16 and VGGNet-19, and they have contributed significantly to precision agriculture. For instance, Thakur et al. [64] developed a lightweight CNN based on VGGNet-16, named 'VGG-ICNN', for maize, apple and rice crop diseases identification using plant leaf images with 99.16% accuracy. Additionally, Ishengoma et al. [65], Fan and Guan [66], Subramanian et al. [67], Tian et al. [68], and Waheed et al. [69] employed VGG-16 as back-born of their model and achieved 97.29%, 98.3%, 99.21%, 96.8%, and 99% accuracy respectfully, for maize leaf infected detection. Furthermore, VGG-16 was further deepened by adding three extra convolutional layers, resulting in the introduction of VGG-19 architecture. These extra layers allow VGG-19 architecture to learn more intricate features and potentially capture more detailed information from the input. The works in [70], [71], and [72] achieved 94.22%,99.73%, and 94% accuracy, respectively using VGG-19 architecture for detecting crop pests and disease. Furthermore, Paul et al. [73] used VGG-19 algorithm to detect and classify tomato leaf diseases and obtain 95% accuracy, 89% Recall, and 92% F1-score. Despite VGGNet's simplified architecture, deeper networks and enhanced feature extraction capability compared to its predecessor, it still requires more computational resources and long computational runtime for training due to its deeper network.

4) RESNET

As CNN architectures become extremely deeper, issues such as vanishing gradients and a large number of parameters to train rise. These issues lead to increased overfittings, computational resources and reduced accuracy. To tackle these problems, He et al. [74] introduced the ResNet architecture in 2015. ResNet utilizes skip connections, also known as residual connections, to address vanishing gradient issue. By allowing the network to learn residual mappings, ResNet effectively overcomes the vanishing gradient problems and enable the training of much deeper networks. The overall architecture of ResNet is presented in Fig.6.

This architectural innovation has significantly improved crop affliction detection, allowing the identification of intricate patterns and subtle signs indicative of various diseases and pests affecting plants. Notably, Hassan and Maji [75], Xu et al. [76], Kumar et al. [77], Zeng et al. [78], Wang et al. [79], Masood et al. [80] and Rachmad et al. [81] utilized ResNet architecture in their studies, achieving remarkable accuracy rates of 96%, 96.02%, 93.5%, 92.9%, 98.52%, 97.89% and 95.59%, respectively, in identifying

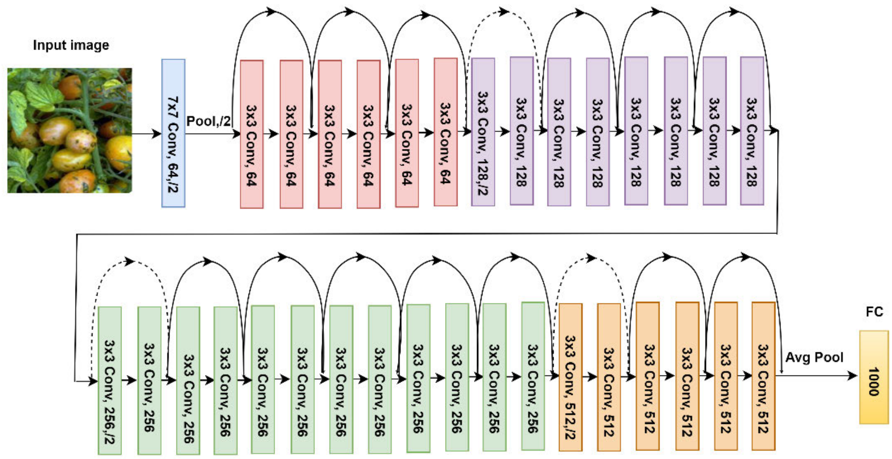


FIGURE 6. Generic architecture of ResNet [74].

various crop pests and diseases. Furthermore, Hassan and Maji [75] employed two parallel attention mechanisms in ResNet architectures and achieved 86.9% accuracy, 100% Recall, and 97% F1-score. These results highlight the architecture's accuracy in classifying complex afflictions. However, while the use of skip connections has eliminated vanishing gradient problems and enabled the training of extremely deep networks, it faces other challenges such as increased design complexity, longer training time and higher memory consumption due to skip connections.

5) DENSENET

A deep convolutional architecture characterized by densely connected layers, named DenseNet, which is presented in Fig.7, was introduced by Huang et al. [82] in 2026. It promotes the feature reuse and facilitates gradient flow throughout the network, allowing more effective information propagation and enhanced feature extraction in an image.

In the precision agriculture, Meena et al. [83], Iparraguirre-Villanueva et al. [84], Chen et al. [85], Bakr et al [86], Amin et al. [87], Vellaichamy et al. [88], Albattah et al. [89], and Waheed et al. [90] harnessed the power of DenseNet in their studies, and achieved remarkable accuracies of 99.6, 98%, 98.50%, 99.70%, 98.56%, 94.96%, 99.982% and 98.06%, respectively in identifying common pests and diseases in plant. The dense connectivity and feature reuse mechanisms in DenseNet demonstrate its ability to effectively capture intricate patterns in both diseases and pests affecting agricultural crops. This is evidenced by their aforementioned accuracies, which are relatively superior to those provided by ResNets and other previously discussed CNN architectures. However, high computational resources, due to dense connectivity, especially in extreme deep network is still a challenge for DenseNet based algorithms.

6) MOBILENET

To further overcome computational resource requirements and latency problem, in 2017, Howard et al. [91] presented MobileNet, a high accurate, real-time processing, light-weight and low power consumption model suitable for edge deployment in mobile devices such as UAV, mobile devices and ground robots.

The MobileNet's key innovation involves depth wise and pointwise separable convolutions which significantly reduces computational complexity by reducing the number of parameters compared to traditional CNNs, while preserving accuracy. Its typical architecture representation is depicted in *Fig.9* along with *Fig. 8 (a)* and *Fig. 8 (b)* [91], [92], illustrating the standard convolution layer block and depth-wise separable convolution layer block, respectively.

In the domain of precision agriculture, Barman et al. [93], Ma et al. [94], Chen et al. [95] and Bi et al. [96] used MobileNet architecture to detect various corn pests and leaf diseases, and achieved accuracies of 93.75%, 98.21%, 99.85% and 98.23%, respectively. Furthermore, light-weight models based on MobileNet architecture were developed in [97], [98], [99], [100], and [101], and their deployment empowered field-deployable devices and drones equipped with cameras to swiftly process images. Despite reduced computational complexity and real-time applications, MobileNet based models have reduced accuracy compared to large and complex models due to the need for balancing accuracy with efficiency.

7) EFFICIENTNET

For further optimization of CNN models' performance and size, EfficientNet was introduced by Shoaib et al. [102]. This advanced architecture, illustrated in *Fig.10*, has revolutionized the landscape of CNN architectures by redefining model scaling through a holistic strategy that harmonizes network depth, width, and resolution. This approach achieved remarkable performance gains without compromising computational efficiency [103].

The EfficientNet architecture series collectively contributed to the state-of-the-art in crop pest image recognition, forming a diverse arsenal of tools to address problems of

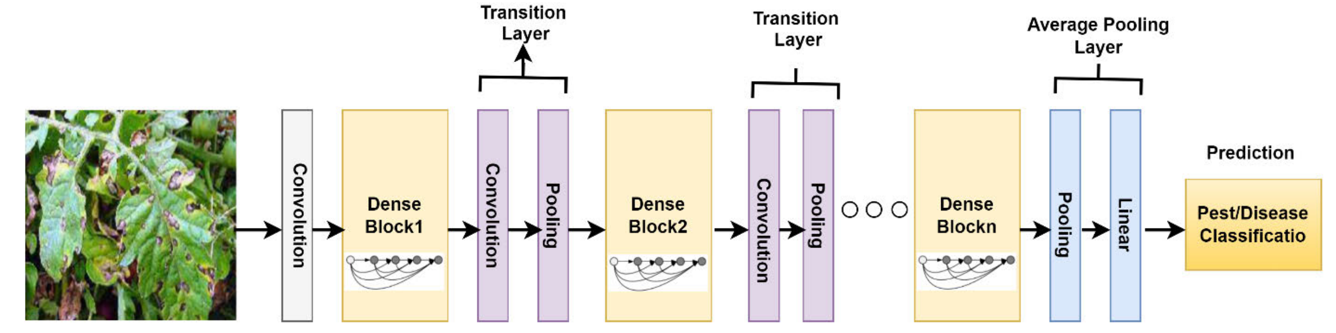


FIGURE 7. Generic architecture of DenseNet [82].

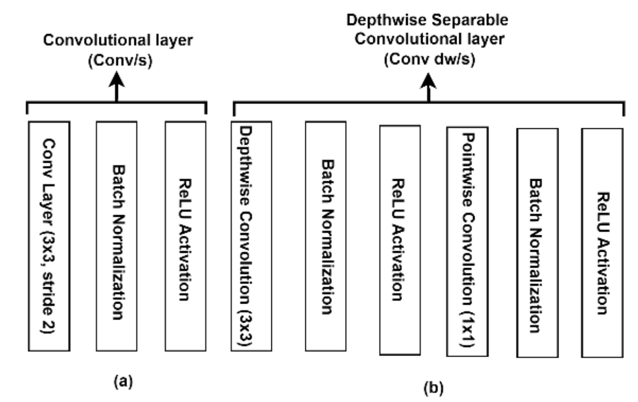


FIGURE 8. (a) standard convolution layer, (b) depth-wise separable convolution layer.

pest detection in agricultural landscapes. Sheema et al. [101], Zheng et al. [104], Singh et al. [105] Liu et al. [106], Adnan et al. [107], Rajeena et al. [108], Shoaib et al. [98] and Albahli and Masood [109] fine-tuned the pre-trained EfficientNet, and achieved 99%, 94%, 91.745%, 98.52%, 98.71%, 98.85%, 94% and 99.89% accuracy, respectively.

When evaluating the performance of image recognition models based on CNN architecture, the predominant and most common metric of choice across these studies is accuracy. While accuracy indicates a general measure of CNN based model's correctness, it may not be the most informative metric especially when dealing with imbalanced dataset or accuracy which falls below certain threshold value, and this may mislead in decision making. Therefore, when these happen, its crucial to consider additional performance metrics such as recall and F1-score to provide more insights and delve deeper into model's performance. Recall and F1-score offers more understanding of the model's ability to correctly identify positive cases (sensitivity), while minimizing false positives, which is crucial for effective decision-making in pest and disease management. Table 1 summarizes DL models based on CNN architecture for image recognition applied in pest and disease detection, highlighting their performance measures, strengths and limitations.

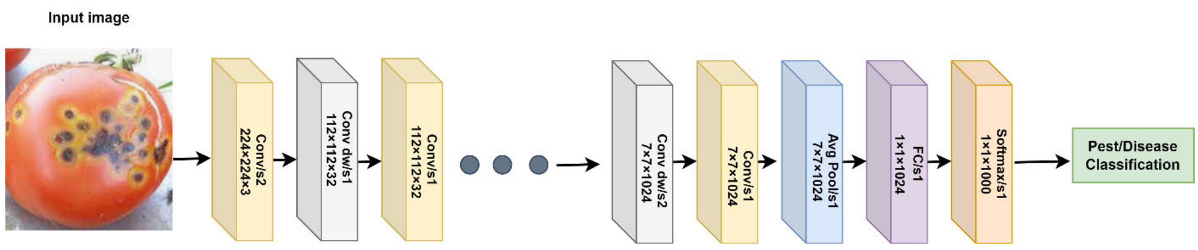
B. DL/CNN-BASED OBJECT DETECTION ARCHITECTURES AND ITS APPLICATION IN PEST AND DISEASE DETECTION

The diagram in *Fig.11* illustrates a general structure of an object detection architecture, combining two different object detectors. The upper part of the diagram illustrates the two-stage object detector while the lower part illustrates one-stage object detector. In a two-stage detector, once the feature extraction backbone block has extracted all necessary features from the input image into feature maps, the Region Proposal Network (RPN) block takes the lead. It is tasked with identifying potential regions of interest (ROIs) within the feature maps, flagging areas that might contain objects in form of bounding boxes. Finally, the detector classifies that proposed regions in bounding boxes into classes along with corresponding class prediction probabilities. On the other hand, the one-stage detector takes feature maps and directly predicts bounding boxes and corresponding class probabilities [112].

The emergence of object detection techniques in DL has significantly advanced precision agriculture practices [113], particularly, it has led to remarkable strides in accurate identification and localization of pests and diseases affecting plants [114]. The most prominent object detection architectures, include Faster R-CNN, YOLO, SSD, Mask R-CNN and EfficientDet [115], show substantial promise in revolutionizing crop pest and disease detection. They offer precise and efficient detection capabilities crucial for proactive crop management and ensuring proper health of the growing plants [116].

1) FASTER R-CNN

Since the invention of Region-based Convolutional Neural Networks (R-CNN) in 2014 by Girshik et al. [117], computer vision has entered new era of object detection and localization within images. This was achieved by proposing R-CNNs for accurate localization and classification of objects in images. Built on R-CNN concept, Ren et al. [118] introduced Faster



(c)

FIGURE 9. Generic architecture of MobileNet [91].

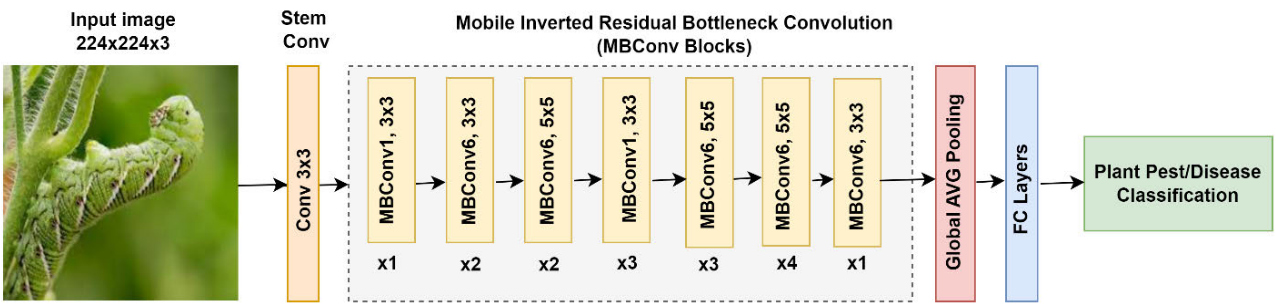


FIGURE 10. Generic architecture of EffientNet [102].

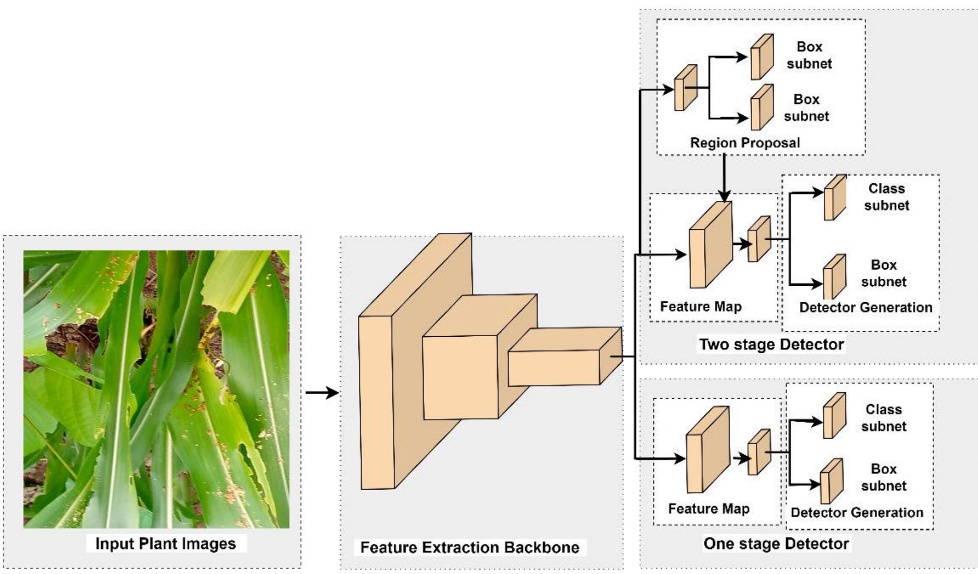


FIGURE 11. Overall object detection architecture combining one -stage and two-stage detectors for plant/pest detection.

R-CNN architecture that uses the Region Proposal Network (RPN) to simultaneously predict object bounds and objectness scores at each position as illustrated in *Fig.12* below.

In the domain of agricultural research, Faster R-CNN algorithms have been employed for pest and disease detection in real-time with high precision. Studies by Quan et al. [119] and Zhang et al. [120] showcased the efficacy of Faster R-CNN to accurately identify corn seedling and stand counting with 97.71% and 99.8% mean average precision rates, respectively. Similarly, studies in [121] and [122] investigated Tessel Detection Convolution Neural Network (TD-CNN) based on Faster R-CNN, leveraging low

TABLE 1. Summary of advanced DL/CNN based image recognition architectures for plant pest and disease detection.

CNN architecture backborn	Number of parameters (in Million)	Model name	Accuracy (%)	Recall	F1-score	Ref	Year	Main contribution and limitation
AlexNet	60 – 65 M	MS-Robust AlexNet	98,6	>96	> 97	[51]	2020	Breakthrough in DL for large multi-class classification with improved accuracy. - Over fitting problems and high computational resources requirements. - Training time is very high
		TCI-ALEXN	93.2	>96	>92	[52]	2021	
		AlexNet	93.5	95.08	93.5	[53]	2020	
		Sustomized AlexNet	98.33	-	-	[54]	2021	
			98	99	98	[55]	2022	
GoogLeNet	6 –10 M	GoogLeNet	98.05	98.02	98.03	[57]	2020	- Inception concept for computational efficiency and enhanced accuracy - Complexity in design due to complex inception modules
		GoogLeNet/Alex Net	99.3	99.19	99.18	[58]	2016	
		GoogLeNet, Cifar10	98.9	-	-	[60]	2018	
		Inseption-V3	97.0	-	-	[61]	2019	
VGGNet	138 –148 M	VGG-ICNN	99.6	-	-	[64]	2023	- Simplified architecture with deeper networks, reduced depth (small size filters), enhanced feature extraction and improved accuracy. - Higher computational resources and training time due to deeper network.
		VGG-16,VGG-19	96	96	97	[65]	2021	
		VGNet	98.3	98.6	-	[66]	2023	
		VGG-16	97	>94	>94	[67]	2022	
		VGG-16	96.8	-	-	[68]	2019	
		VGG-16	96	98	75	[69]	2022	
		VGG-19	99.7	99.9	99.59	[71]	2022	
		VGG-19	94.22	94.58	93.07	[70]	2019	
		VGG-16,VGG-19	95	89	92	[73]	2023	
ResNet	25 – 60 M	ResNet50	96.0	-	-	[75]	2023	- use of skip connections to eliminate vanishing gradient problems, enabling the training of extremely deep networks and improved accuracy - Increased complex design, training time and memory consumption due to skip connections
		ResNet50+Faster R-CNN	93.5	-	-	[76]	2022	
		SKPSNet-50	92.9	-	-	[77]	2022	
		ResNet-50,	97.8	-	-	[78]	2021	
		MaizeNet	97.8	>97.5	>97.7	[79]	2023	
		ResNet-50	95.5	-	-	[80]	3023	
		ResNet50-SA	96.68	100	97	[81]	2024	
DenseNet	8 – 20 M	DenseNet-201	98	98	98	[83]	2023	- Enhanced information flow with reduced parameter, and reduced vanishing gradient problems, by enhancing feature reuse concept. - High computational resources due to dense connectivity, especially in extreme deep network
		MobileDANet	98.5	97	97	[84]	2020	
		DenseNet-201	98.7	97	97	[85]	2022	
		DanseNet121+EfficientNetB0	98.5	>95	>94	[86]	2022	
		DenseNet-121	94.9	-	-	[87]	2021	
		DenseNet-77	99.9	99.9	99.9	[88]	2022	
		Optimized DenseNet	98	>96	>97	[89]	2020	
		Fine-tuned DenseNet	99.62	-	-	[90]	2024	
MobileNet	4 – 5 M	MobileNet	93.7	-	-	[93]	2021	- use depth wise separable convolutions to create lightweight, efficient and reduced computational complexity model with reasonable accuracy
		I-CBAM-MobileNetV2	98.2	>95	>96	[94]	2023	
		MobileNet-Beta-MobileNet-V2	99.8	98	99	[95]	2020	
		CD-MobileNetV3	98.2	98.26	98.26	[96]	2023	

TABLE 1. ***(Continued.)*** **Summary of advanced DL/CNN based image recognition architectures for plant pest and disease detection.**

		MobileNet V3-Small	79.5	77.91	98.62	[100]	2023	suitable for deployment on resource-constrained devices such as mobile devices. - Reduced accuracy compared to large and complex models due to the trade-off between accuracy and efficiency.
		enhanced MobileNet	95.94			[99]	2023	
Efficient-Net	5 – 10 M	Fine-tuned EfficientNet	98.5	98	98	[106],	2020,	- Utilize compound scaling to optimize depth, width and resolution to achieve high performance while balancing accuracy and computational resources. - The model performance is reduced due to computational resource constraints and the need to balance accuracy with efficiency.
			98.8	-	-	[108]	2023	
		EGWT	94	94	95	[104]	2024	
		EfficientNetB3	98.7	98.71	98.72	[107]	2023	
		EANet	99.8	-	-	[109]	2022	
		EfficientNetB6	91.74	-	-	[105]	2022	
		PCNet	94	-	-	[98]	2023	
		EfficientNetB5	99.06	99%	99%	[109]	2024	
		EfficientNetB3-AADL	98.71	98.71	98.72	[107]	2023	

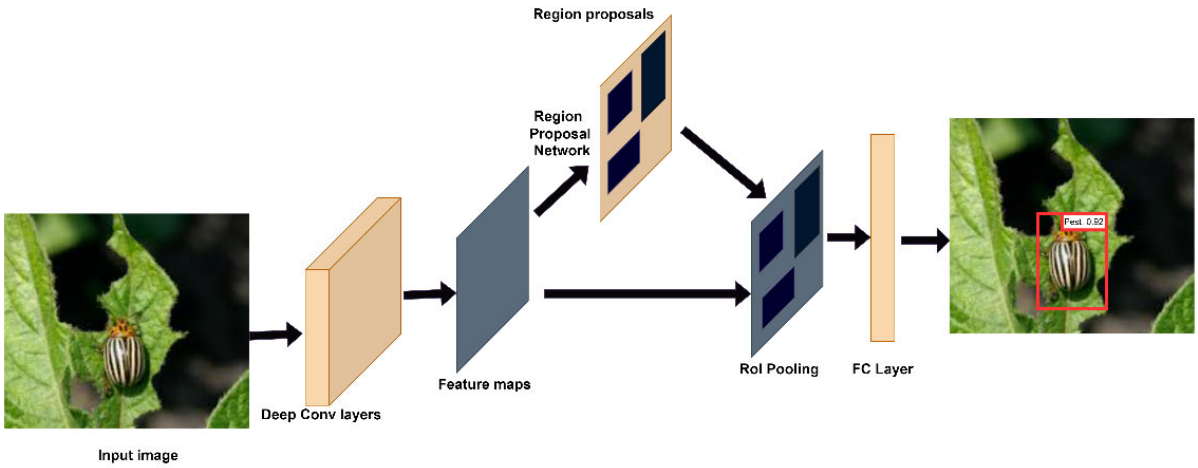


FIGURE 12. Generic architecture of Faster R-CNN [117].

altitude UAV imagery platform, and achieved mean average precision rates of 91.78% and 95.9%, respectively. In another study [123], researchers combined IoT technology and Faster R-CNN algorithms to identify the infestation density of Fall Armyworm (FAW) in maize plants, achieving an accuracy of 98%. Furthermore, the improved Faster R-CNN models developed by [80] and [124] exhibited remarkable capabilities for detecting and localizing pest infestation in corn leaves, achieving accuracies of 97.89% and 91.83%, respectively. Despite its significant performance, Faster R-CNN faces challenges in detecting very small pests, and requires significant computational resources due to its two-stage detection process.

2) MASK R-CNN

Mask R-CNN is a revolutionary extension of the Faster R-CNN architecture, which includes additional branch for predicting object masks alongside the existing branch for bounding box recognition. Introduced by Girshick et al. [125] in 2017, it has greatly enhanced the capabilities of object detection, by accurately identifying and segmenting multiple objects within an image with high pixel-level precision. The *Fig.13* depicts the fundamental architecture of Mask R-CNN.

In precision agriculture, Mask R-CNN has been utilized for detecting pests like Fall Armyworm in maize crops, achieving an accuracy of 94.21 % [126]. Craze et al. [127], further reconstructed R-CNN model for identifying corn gray leaf spot disease, achieving a 94.1% accuracy when trained with Plant Village dataset. Moreover, Pang et al. [128] and Gao et al. [129] integrated Mask R-CNN model with UAV-based imagery systems for early-season plant stand counting, achieving remarkable segmentation accuracy scores of 95.8% and 98.87%, respectively. In further advancements, Aijun et al. [130] utilized Mask R-CNN models for corn

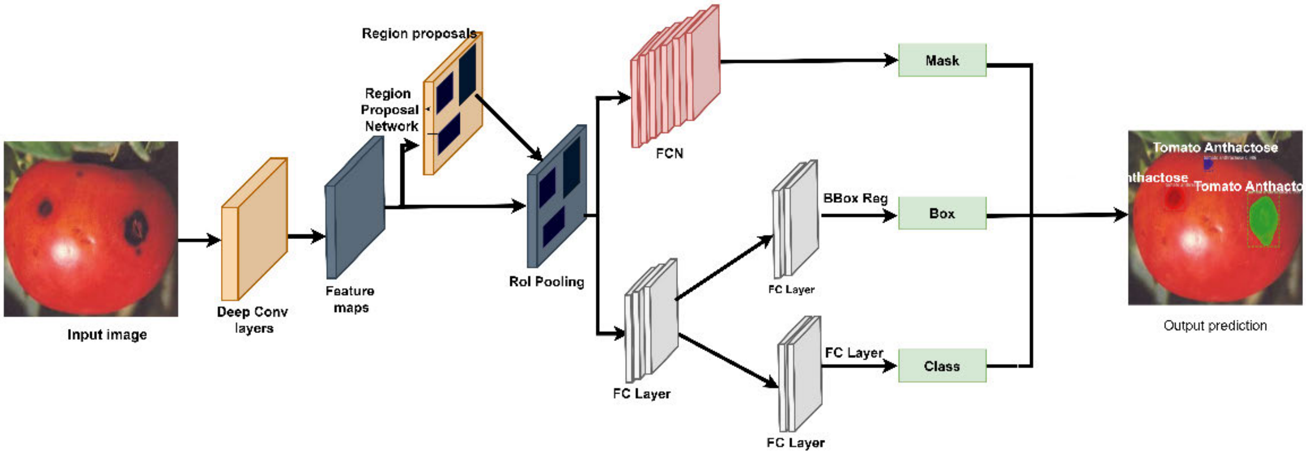


FIGURE 13. Generic architecture of Mask R-CN [125].

ear harvesting and corn cob image classification, achieving an average accuracy of 94.3%. Deepika and Arthi [131] developed an improved MaskFaster Region-Based Convolutional Neural Network (IMFR-CNN) method that detects four different types pests and achieved 99% accuracy. However, the Mask R-CNN model is computationally intensive and struggles to detect extremely small pests.

3) SSD

For further advancement in enhancing object detection accuracy and efficiency, in 2016, Liu et al. [132] introduced a Single Shot MultiBox Detector (SSD). It utilizes a single neural network to predict bounding boxes and class probabilities across various scales and aspect ratios in a one pass. It achieves this by employing a set of default boxes connected to different feature maps for real-time detection [133]. The basic architecture of SSD is illustrated in *Fig.14*.

Building upon this foundation, Sun et al. [124] improved original SSD model and proposed a multi-scale feature fusion instance detection method for detecting plant leaf disease and achieved 91.83% mAP. Jiang et al. [134] developed INAR-SSD model that uses GoogLeNet inception module for feature extraction to detect apple leaf diseases with 78.80% mAP. Similarly, MEAN-SSD model was proposed by Sun et al. [135] to be deployed in mobile device and it was trained on apple leaf disease dataset which attained 83.12% mAP. Furthermore, a deep block attention SSD (DBA_SSD) network model was presented in [136] that fine-tuned the original SSD algorithm with residual network and attention mechanism for plant leaf diseases detection, achieving improved accuracy of 92.20%. However, the SSD models has problems of decreasing the resolution of the images to a lower quality and difficulties for detecting very small pests or symptoms.

4) YOLO

YOLO (You Only Look Once) architecture, introduced by Redmon et al. [137], is a unified framework and real-time object detection technology that reduces redundant calculations and optimizes computational resources.

As depicted in *Fig.15*, YOLO system has a single-shot detection mechanism that makes predictions all at once without the need to separate the region proposals, allowing for faster training and inference [138]. In the context of plant pest and disease detection, Ma et al. [139] and Leng et al. [140] employed YOLO-V5 object detection framework for detecting and localizing infected area on crop leaves, achieving accuracy rates of 95.2% and 87.5%, respectively. YOLO, YOLO-V5 and YOLO-V8 models integrated into mobile devices were explored in [141], ([142] and [143], achieving accuracy rates of 85.4%, 99.43% and 99.04%, respectively. Furthermore, insects affecting corn crop were detected and identified using YOLO based algorithms including YOLO-PPLCBot [144] with 95.3% mAP, AgriPest-YOLO [145] obtaining 71.3% mAP, and Maize-YOLO [146] achieving 76.3% accuracy. However, YOLO based models face challenges in detecting very small pests within plant images or videos due to the lower recall rates, as well as detecting multiple pests that are extremely close to each other due to the limitations of bounding boxes.

5) EFFICIENTDET

For further improving the scalability and efficiency of object detection models, Tan et al. in 2020 [147] proposed an EfficientDet, an advanced architecture illustrated in *Fig.16*. While EfficientDet compromises model accuracy, it enhances computational efficiency. The EfficientDet simultaneously balances the resolution, depth, and width of all backbone, feature network as well as box/class prediction networks. By employing backbones such as EfficientNet, ResNet and MobileNet to enhance its performance, EfficientDet achieves higher efficiency for resource-constrained applications.

In the realm of precision agriculture, Liu et al. [148] proposed the EFDet model, designed specifically for efficient detection of cucumber leaves diseases. Leveraging an efficient backbone network, feature fusion module, and

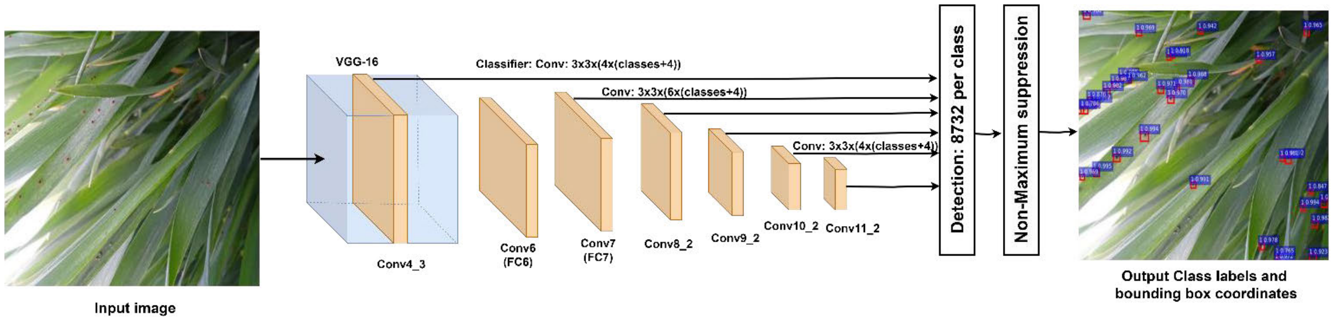


FIGURE 14. Generic architecture of SSD [132].

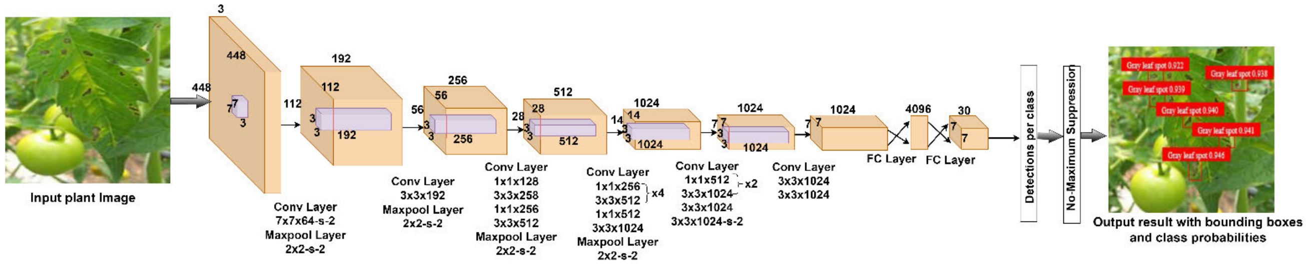


FIGURE 15. Generic architecture of YOLO [137].

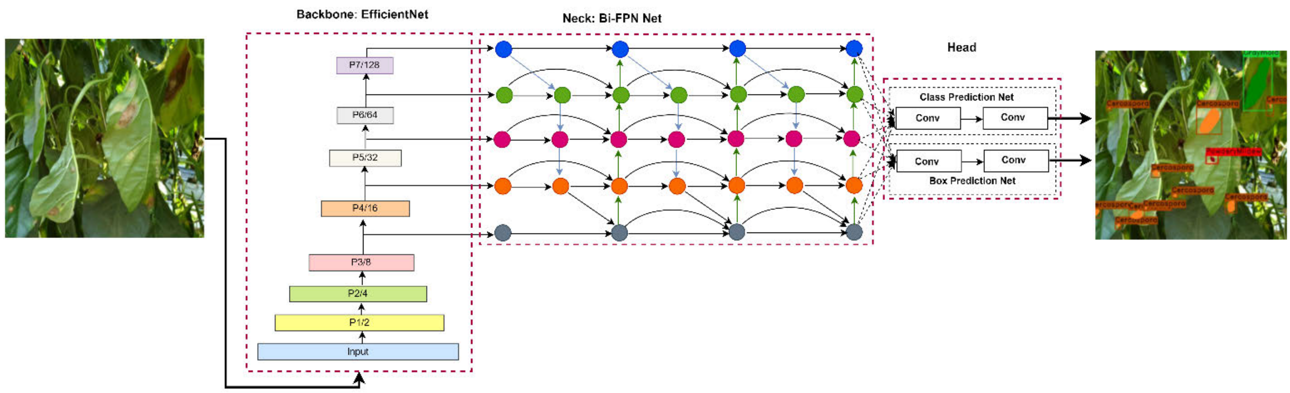


FIGURE 16. Generic architecture of EfficientDet [147].

predictor, the model enhances detection accuracy, achieving 85.52% mAP with a compact 7.72MB model size. Another lightweight model suitable for handheld devices, based on EfficientDet framework, was developed by Lakshmi and Savarimuthu [149]. Employing transfer learning-based EfficientDet, it attained a mean Average Precision (mAP) of 74.10%, boasting fewer parameters compared to SSD, Faster-RCNN, YOLOv3, RetinaNet and Mask-RCNN architectures. Similarly, in the work by [150], an EfficientDet based model with state-of-the-art feature extractors such as EfficientNet, ResNet50 and MobilenetV2 as a backbone, was developed for detecting paddy rice seedlings. Comparative analysis with existing object detection architectures showed that the developed model outperforms others with 83% mean average precision. Furthermore, Niyigena et al. [151] developed an EfficientDet model for detecting and classifying Scirtothrips dorsalis Hood pests from other types of pests on the yellow sticky traps. Compared to YOLOv5, Faster R-CNN, SSD, and MobileNetV2, this model achieved a superior 93.3% mAP with 13.5 MB model size, indicating its suitability for mobile, IoT device and other computational resource constraint applications.

C. INTEGRATION OF IOT WITH DL ARCHITECTURES FOR PEST AND DISEASE DETECTION

The integration of IoT with AI technology has significantly advanced the precision agriculture, particularly in crop health monitoring [154], [155]. In domain of computer vision, the state-of-the-art DL based image recognition and object detection architectures, coupled with IoT technology [156],

TABLE 2. Summary of advanced DL/CNN based object detection architectures for plant pest and disease detection.

CNN architecture	Number of parameters	Model name	Mean Average-Precision (mAP, %)	Accuracy (%)	Recall (%)	F1-score (%)	Ref	Year	Main contribution and limitations
Faster R-CNN	40 – 45M	Faster R-CNN	97.71	-	98	96	[119]	2019	- Introduced region proposal network (RPN) for improved region proposal generation, achieving balanced speed and accuracy. - Exhibits high precision for detection and localization of pest/disease infection in images. - Struggles to detect very small pests, and it is computationally intensive due to its two-stage detection. - Slower than single stage detector due to its two-stage approach.
		Faster R-CNN	99.9	-	-	-	[120]	2020	
		Faster R-CNN	91.78	-	98.32	97.9	[121]	2020	
		TD-CNN	97.64	97	98.52	97.9	[122]	2021	
		SWFRN	98	98	>95	>93	[123]	2022	
		MaizeNet	97.89	97.89	97	97	[80]	2023	
		SSD+MT+RPN+GIoU512	91.83	-	-	-	[124]	2020	
Mask R-CNN	40 – 50M	Mask R-CNN	94.21	-	-	-	[126]	2023	- Introduced mask-based detection technique for offering more detailed object localization and segmentation. - Suitable for high precision in identification and segmentation of pests/diseases, allowing more accurate localization of affected areas in plant images. - Computationally intensive and struggle to detect extremely small pests.
		GLS-Net	94.1	94.1	94.1	93.7	[127]	2022	
		MaxArea Mask Scoring RCNN	95.8	95.8	-	-	[128]	2020	
		Mask R-CNN	98.87	98.77	-	-	[129]	2023	
		MASK-RCNN	94.3	94.3	-	-	[130]	2022	
		IMFRCNN	99	99.2	100	100	[131]	2022	
SSD	20 – 40M	SSD	91.83, 96.89	-, -	-	-	[132], [133]	2020, 2021	- Offers a single-stage object detection capability that provides a good balance between speed, efficiency, and accuracy. - Suitable for high precision and real-time crop pest/disease detection
		INAR-SSD	78.80	97.14	-	-	[124]	2019	
		MEAN-SSD	83.12	97.07	97.8	97.6	[134]	2021	
		DBA-SSD	92.20	92	-	-	[135]	2021	
		modified SSD	85%	91	91	91	[136]	2023	
YOLO	40 – 60M	Improved YOLOv5n	95.2	95	94.9	-	[139]	2023	- With its Single Shot Detection capability, it efficiently processes the entire image only once to detect and localize pests and disease signs. - Thanks to its high speed of detection, lightweight design and impressive accuracy, it is suitable for pest and disease detection in settings with limited resources, such as embedded devices, drones, and IoT devices. - However, it struggles with detecting very small pests in plant images, as well as detecting multiple pests that are clustered closely together due to the limitations of bounding boxes.
		CEMLB-YOLO	87.5	-	79.3	-	[140]	2023	
		YOLO-V5	99.43	-	-	-	[141]	2022	
		YOLO-V8	99.04	-	87.66	-	[142]	2023	
		YOLO-PPLCBot	95.3	-	97	92.1	[143]	2023	
		AgriPest-YOLO	71.3	-	-	-	[144]	2022	
		Maize-YOLO	76.3	-	77.3	75.2	[145]	2023	
		YOLO-Faster-RCNN	85.2	85.4	-	-	[146]	2023	
EfficientDet	3 – 10 M	EFDet	85.52	-	-	-	[147]	2021	- With its lightweight design and high accuracy architecture with fewer computational resources, it is suitable for resource constrained applications like mobile, embedded devices, IoT devices, and drones. - However, it faces difficulties in detecting extremely small pests.
		EfficientDet-D2	74.1	-	94	90.9	[148]	2022	
		EfficientDet	83	-	0.71	0.77	[149]	2022	
		EfficientDet	93.3	-	-	-	[150]	2023	
		Fuzzy EfficientDet	94.29	-	89.4	91.65	[151]	2024	

offer dynamic advancements in Smart agricultural devices. This enables real-time monitoring and precise identification of various crop threats, including invasive pests and plant diseases. This section explores the potential of integrating IoT driven technologies with diverse DL architectures by highlighting their roles in advancing pests and diseases prediction and early identification within agricultural landscapes [157], [158].

The diagram in Fig.17 illustrates an overview of a typical IoT system integrated with DL/CNN algorithm for pest and disease detection applications. It begins with the IoT device, such as drone or mobile device equipped with camera sensors, collecting data (plant images) from the field. These images are either processed directly at the edge or transmitted to the cloud platform containing DL/CNN algorithms, which have been trained for analysis. The DL/CNN algorithms analyze the input images, classify them, and make decision accordingly. The results are subsequently sent to or visualized on the cloud platform, where they can be accessed by farmers or other stakeholders.

1) DL ALGORITHMS INTEGRATED WITH UNMANNERED AERIAL VEHICLE (UAV) BASED IOT PLATFORM FOR CROP PEST AND DISEASE DETECTION

The integration of UAV platform with IoT technology, coupled with DL algorithms mark a new paradigm in precision agriculture, enabling intelligent crop health monitoring applications [40], [159]. UAVs equipped with IoT sensors collect real-time data on crop health and environment conditions crucial for early detection and identification of crop pests and diseases that hinder crop development [160]. The data gathered by this IoT-driven UAV setup is processed by DL algorithms at the edge of the network or at the cloud centered platforms for real-time data-driven decision making.

Recent research efforts have focused on leveraging the synergy of UAVs, IoT and DL technologies to alleviate the damage caused by invasive pests and diseases. For instance, Gao et al. [161] implemented an UAV system equipped with IoT spectral camera sensors for crop pests damage detection. Saranya et al. [162] utilized UAV based IoT for detecting and classifying crop leaf pests, using fine-tuned VGG-16 model fused with dense layers, achieving an impressive accuracy of 96.58 %. Similarly, Khan et al. [163] integrated a UAV and YOLOv5-based model, incorporating advanced attention modules, and refining multiscale feature extraction techniques, achieving 95% mAP. Refaai et al. [160] presented an IoT-based UAV system for pests and diseases identification, evaluating nine DNN architectures for their effectiveness, with ResNet50 and Support Vector Machine models being the highest performers, achieving 97.86% accuracy. Chen et al. [164] implemented an IoT powered UAV system, embedded with Tiny-YOLOv3 model for real-time pest detection, using drone to optimally spray pesticides, yielding promising results with 95.33% precision.

2) DL ALGORITHMS INTEGRATED WITH MOBILE DEVICE BASED IOT FOR CROP PEST AND DISEASE DETECTION

Studies that integrate mobile devices such as smartphone, IoT, and DL hane propelled advancements in precision agriculture. In the study by Hu et al. [165], a combination of IoT and DL technologies was used to build a smart crop fine-grained disease identification called Multidimensional Feature Compensation based on Residual Neural Network (MDFC-ResNet). Their system achieved 85.22% accuracy, with results delivered to farmers via smartphone. Jiang et al. [134] employed DL model based on Single Short Detection inception module and rainbow concatenation model named INAR-SSD, which can be integrated in mobile devices to detect five apple diseases with 78.80% mean average precision. Additionally, a smartphone have been used for Tessaratoma papillosa pests identification in rice farm [166], leveraging IoT- integrated DL algorithms like YOLOv3 algorithm integrated with IoT technology to achieve 90% accuracy.

In another work, Chen et al. [167] developed a scalable pest detection system employing smartphone embedded with DL- based object detection model and IoT technology to send data to the cloud platform. Faster R-CNN, SSD, and YOLOv4 were compered and YOLOv4 outperforming others with 100% accuracy when deployed in the field. Moreover, a mobile app was developed for real-time Brown spot disease detection in rice paddies in [168]. The system employs CNN architectures integrated with IoT technology, achieving a commendable accuracy of 97.70%. A novel oilseed rape pest detection algorithm was developed by He et al. [169]. In this study, 12 types of oilseed rape pests were classified, and different object detection architectures were compared, including Faster-CNN, R-FCN and SSD, with SSD demonstrating higher performance with a 77.14% mAP. Finally, Dhanaraj et al. [170] proposed an IoT based remote- controlled system that employs a DL algorithm at the edge of the network to detect crop pests affecting plants. In this work, various DL algorithms, including DenseNet, VGG-16, YOLOv5, DCNN, ANN, KNN, Faster RCNN, and ResNet-50 were compared, with DMF-ResNet outscoring others with 99.75% accuracy.

3) IoT SCHEME FOR AUTONOMOUS UAV FOR PEST AND DISEASE DETECTION AND CONTROL

D. DATA ACQUISITION AND ACTUATION LAYER

This layer involves the components responsible for acquiring data (sensing) and taking actions (actuation) on the field. The IoT set-up containing camera sensors, pesticide spraying set-up as actuator and edge processing device is supported by an autonomous UAV, which covers a large area with high precision [171].

1) MOVING PLATFORM: AUTONOMOUS UAV

One of the specialized agricultural UAVs designed for precision farming is DJI Agras T30 drone. It is suitable for pest

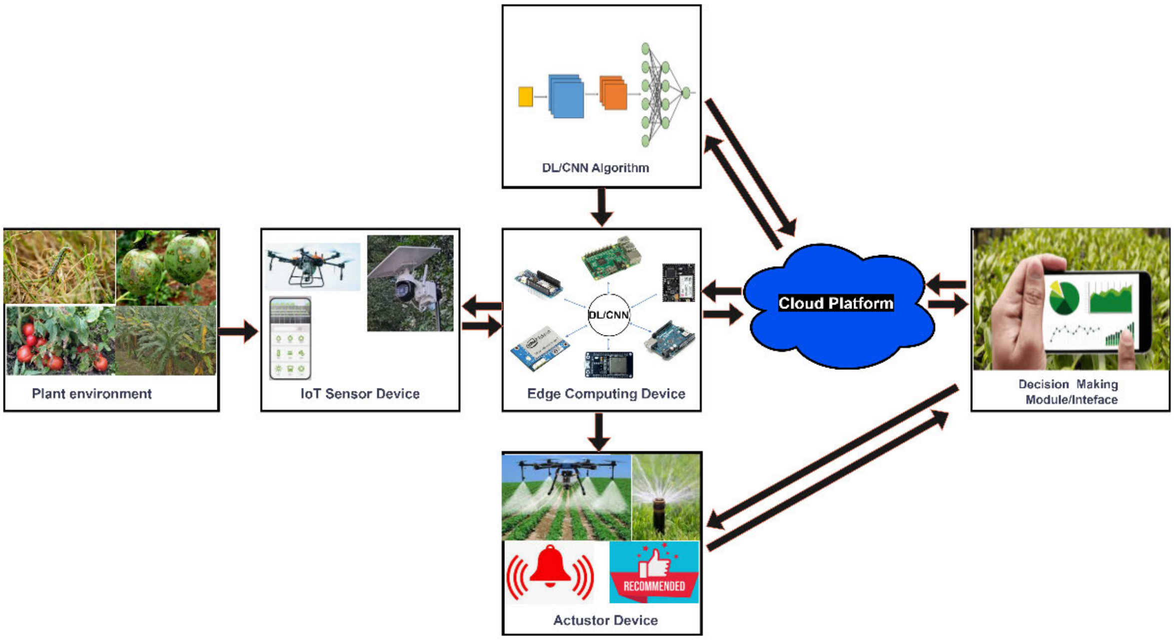


FIGURE 17. General structure of IoT system integrated with DL/CNN for plant pest/disease detection.

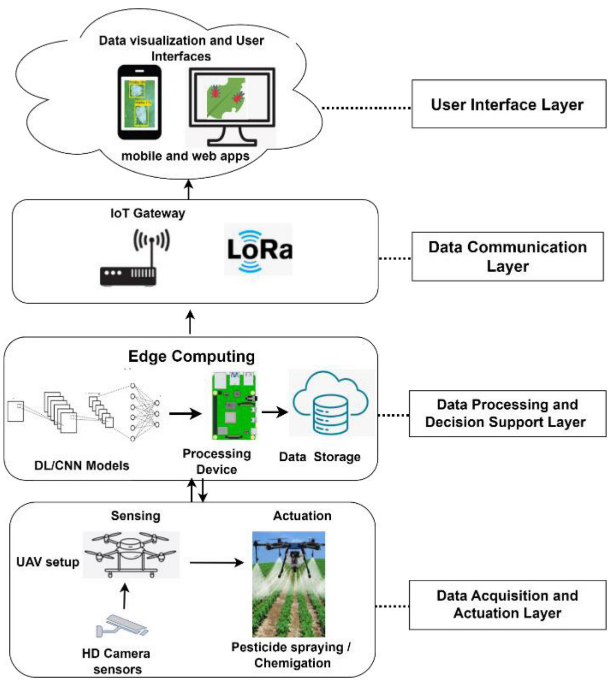


FIGURE 18. IoT scheme for autonomous UAV for pest and disease detection and control.

and disease detection due to its advanced flight capability, large payload carrying capacity, and integrated spraying system [174]. The UAV can cover large areas efficiently and is equipped with a range of sensors and high-definition cameras. Its autonomous features allow for pre-programmed flight paths, ensuring comprehensive coverage, and consistent data collection [172].

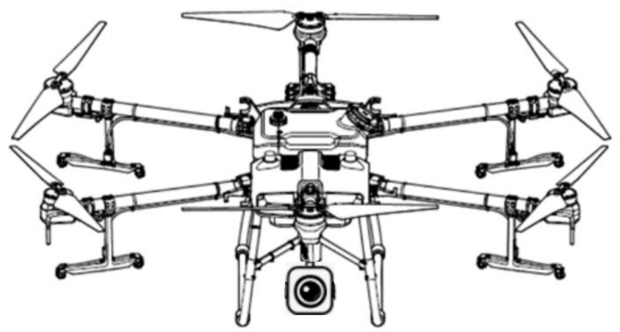


FIGURE 19. DJI Agras T30 [172].

2) SENSING: HIGH-DEFINITION CAMERA

The quality of the images is critical for the accurate application of DL/CNN algorithms in detecting specific pests or diseases. A high-definition camera such as 4K and infrared cameras with multispectral imaging capabilities can provide detailed visual and non-visual data, and they are suitable for identifying crop stress and disease symptoms not visible to the naked eyes, allowing for the detection of early signs of pest and disease infestation [175].

3) ACTUATION: UAV SPRAYING MECHANISM

The specialized UAV is equipped with a spraying system to apply pesticides directly to the affected areas identified by the sensing component [176]. This allows for targeted intervention, reducing the use of chemicals and minimizing environmental impact. For example, DJI Agras T30 has a high pesticides carrying capacity with a high-precision spraying system that can be adjusted based on the severity of the detected pest or disease [177].

E. DATA PROCESSING AND DECISION SUPPORT LAYER

This layer is responsible for processing data collected by the UAV and making informed-decisions based on that data. An edge computing device integrated with advanced DL models is used to enable real-time data processing, reducing the latency associated with sending data to the cloud for processing.

1) PROCESSING DEVICE: RASPBERRY Pi 5

The System on Chip (SoC) based device such as Raspberry Pi 5 serves as the edge computing device onboard the UAV [178]. It processes the data collected from the high-definition camera using DL/CNN models to detect pests and diseases in real-time. The Raspberry Pi 5 is suitable for edge computing due to its compact size and lightweight model, processing power that support complex and powerful DL models as well as energy efficiency capacity, that make it ideal for integration into an IoT ecosystem [179].

2) DEEP LEARNING/CNN MODELS

The DL models based on CNN architecture such as EfficientNet, MobileNet and Inception series are mostly used due to their high efficiency, balancing accuracy and computational efficiency, making them ideal for deployment on edge devices like the Raspberry Pi 5 [180]. They are capable of accurately identifying pests and diseases from the images captured by the UAV.

3) DATA STORAGE

The raw and processed data, including images of infected and healthy plants and their locations, is stored locally on the edge device or transferred to external storage devices. This data can be used for further analysis or historical record-keeping. A 128GB microSD card are commonly used for local storage, ensuring that sufficient data can be retained even during long missions.

F. DATA COMMUNICATION LAYER

The Data communication layer manages the transmission of information between the UAV supported IoT setup and remote user interface or cloud-based dashboard [181]. This layer ensures reliable data transfer, enabling real-time monitoring and decision-making.

1) COMMUNICATION PROTOCOL: LoRa OR GPRS

For efficient and reliable data communication, LoRa (Long Range) is mostly used as wireless communication protocol [181]. It offers long-range data transmission with low power consumption, making it ideal for agricultural IoT applications where UAVs may operate in remote areas, and it supports communication over distances up to 10-15 km, depending on the environment condition. In addition, General Packet Radio Service (GPRS) which is a mobile data service available on 2G, 3G and 4G cellular communication systems, is used as a backup in areas where LoRa coverage is insufficient or when higher data rates are needed [182].

2) IoT GATEWAY

The IoT Gateway serves as a bridge between the UAV and the cloud or central server. It aggregates data from multiple sensors and devices, processes some of the data, and then transmits it to the cloud for storage or further analysis. Furthermore, it provides edge processing capabilities, offering an additional layer of decision support, and it ensures that the data collected by the UAV is seamlessly integrated into the broader IoT network [183].

G. USER INTERFACE LAYER (FOR DATA VISUALIZATION)

User Interface Layer is responsible for data visualization, and it focuses on how the processed data and decision support information are presented to the end-users, such as farmers or agricultural managers.

1) MOBILE APPLICATIONS

The mobile application provides a user-friendly interface for real-time monitoring and control of the IoT based UAV system [184]. Farmers can receive alerts, view live data, and even control the UAV's operations from their mobile devices. It could include features like push notifications for detected pests or diseases, a live feed from the UAV's camera, and options to adjust the UAV's flight path or spraying mechanisms [173].

2) WEB APPLICATION

The web application offers a more comprehensive platform for data analysis, historical data review, and system configuration. It is accessible from any web browser and provides detailed reports and insights based on the data collected by the UAV. It could also offer advanced features like trend analysis, comparison of historical data, and customizable dashboards. It is ideal for agricultural managers who need a broader view of operations and data over time.

H. BENCHMARK DATASETS FOR CROP PEST AND DISEASE DETECTION

In the field of crop pest and disease detection, specifically for computer vision tasks such as image recognition and object detection, various standard datasets have been established to facilitate researchers to get a wide range of High quality, relevant, and Sufficient dataset for training and evaluating DL/CNN models [185]. These datasets are crucial for standardizing research, enabling comparative analysis, and advancing the state-of-the-art CNN models.

TABLE 3. Summary of advanced CNN algorithms integrated with IoT for plant pest and disease detection.

CNN architecture back born	IoT-setup	Objective	Mean Average Precision	Accuracy	Ref	Year	Advantage
VGG-16	IoT-driven UAV	Pest	-	96.5%	[162]	2023	IoT based, edge computing, high precision, light weight model and real time response
YOLOv5	UAV	Pests	95%	91%	[163]	2024	IoT based, edge computing, high precision, light weight model and real time response
ResNet50	IoT-UAV	Pests/Diseases	-	97.8%	[160]	2022	Edge computing and high accuracy but short performance for UAV and heavy model
Tiny-LOYOv3	IoT-UAV	Pests	95.3%	-	[164]	2021	Edge computing, high precision, light weight model and real time response
EfficientNet	Mobile device	Pest	-	98.7%	[109]	2023	Light weight and highly efficient model
MDFC-ResNet/ResNet-50	Mobile Device	Disease	-	85.2%	[169]	2020	Hybrid model, edge computing, hybrid model and moderate accuracy
GoogLeNet/ SSD	Mobile device	Disease	78,80%	95.1%	[170]	2019	Edge computing, light weight model, hybrid model and moderate accuracy
YOLOv3	Mobile device	Pests/Diseases	90%	90%	[166]	2020	Edge computing, light weight model, and very high accuracy
SSD/LOYOv4	Mobile device	Pests	100%	-	[167]	2021	Edge computing, light weight model, hybrid model and very high accuracy
YOLO	Mobile device	Disease	97.70%	-	[171]	2022	High accuracy, lightweight, edge computing model, and suitable for IoT based devices.
SSD	Mobile device	pests	77.14%	-	[179]	2019	IoT based and light weight model suitable for mobile and UAV application. Accuracy not measured
DMF-ResNet	Mobile device	Pests	99.75%	-	[185]	2023	IoT based, light weight and high accurate model suitable for mobile application

Below, we describe some of the most widely recognized datasets [186].

IV. DISCUSSION

The integration of DL architectures with IoT technology has brought significant advancements in detecting and managing crop pests and diseases. This section discusses key findings, gaps, and limitations, as well as future trends and opportunities in domain of precision agriculture for pest and disease detection. It offers insights into the evolution and potential of DL/CNN architectures integrated with IoT for crop health monitoring.

A. KEY FINDINGS

As the development of DL architectures based on CNN evolves from image recognition such as AlexNet to the state-of-the-art as tiny object detection in image such as EfficientDet and SSD, a wide range of CNN models have been developed for pest and disease management applications and each with own trade-offs in terms of accuracy, efficiency, model size and computational resource requirementsand the choice of architecture depends on the specific requirements of the application, including the available resources, deployment environment, and desired performance metrics.

1) PERFORMANCE

Several CNN architectures, including AlexNet, GoogLeNet/ Inception, VGGNet, ResNet, DenseNet, MobileNet, EfficientNet and YOLO have exhibited high accuracy rates ranging from a moderate 86% to nearly100%. For example, accuracies as high as 99.9% have been achieved by VGGNet, DenseNet and MobileNet architectures in detecting and classifying common cereal diseases and pests. These high accuracy achievements depend on size of dataset used [187], optimization and transfer learning techniques employed. However, increasing accuracy results in increased

TABLE 4. Benchmark datasets for CNN Model training in crop pest and disease detection.

Dataset name	Dataset description	Number of images	Dataset location link
PlantVillage	38 different species of pant pests and diseases	Over 54,000	https://github.com/spMohanty/PlantVillage-Dataset
IP102	102 different categories of insect pests	Over 75,000	https://github.com/aimaerspace/PlantPests102
Crop Pest and Disease Detection	22 different categories of pest and diseases	Over 24,000	https://www.kaggle.com/datasets/nirmal-sankalana/crop-pest-and-disease-detection
Fruits 360	131 types of fruits and vegetables.	Over 67,000	https://www.kaggle.com/datasets/motean/fruits
Plant Pathology 2020	Various foliar diseases categories in apple trees	Over 3,600	https://www.kaggle.com/datasets/mutantspore/plant-pathology-2020-preprocessed-images
Cassava DatasetV2	Various Cassava Disease	Over 21,000	https://www.kaggle.com/datasets/ammarali32/cassava-datasetv2
Corn Leaf Infection Dataset	Various corn pests affecting maize crop	Over 16,000	https://www.kaggle.com/datasets/qramkrishna/corn-leaf-infection-dataset
Tomato Disease Dataset	9 different types of diseases affecting tomato crop	Over 18,000	https://www.kaggle.com/datasets/kaustubhb999/tomatoleaf
Citrus Disease Dataset	2 categories of citrus fruits diseases	Over 7,000	https://www.kaggle.com/datasets/jonathansilva2020/dataset-for-classification-of-citrus-diseases

computational cost. Therefore, these high accurate architectures are suitable for tasks where high accuracy and reliability are paramount with available computing resources. Object detection-based algorithms were employed in disease detection but were assessed primarily using mean average precision, which is the weighted mean of precision at each threshold of intersection over union (IoU), averaged across all classes. The weight itself indicates the increase in recall from the previous threshold. The primary motivation has been to minimize costs associated with controlling false positives while simultaneously mitigating false negatives. Mean average precision depends on the set minimum threshold values of IoU. IoU is a measure of how close the predicted bounding box around the detected object is close to the ground truth of the object bounding box. In conventional object detection scenarios like autonomous driving or robot motion, IoU play a critical role. However, when applied to crop pest and disease detection, these algorithms often fail to detect very small pests due to limitations inherent in intersection over union. While both false positives and false negatives are undesirable in pest and disease detection, the intersection over union does not significantly impact the detection objective. Therefore, accuracy and F_1 score may suffice as metrics for optimizing object detection-based DL algorithms for crop pest and disease detection

2) COMPUTATIONAL RESOURCES

The advanced CNN architectures have different computational resource requirements. Early CNN architectures such as AlexNet, VGGNet and GoogLeNet exhibit moderate to large computational resources requirements as they are characterized by deeper networks with dense layers and large number of parameters. On other hand, MobileNet, EfficientNet, and YOLO architectures employ mode scaling, depth wise separable convolution and single-shot detection techniques, respectively, to reduce computational resources at the expense of reduced accuracy. Therefore, these lightweight models are suitable for resource constraint environment including IoT devices and edge computing platforms such as UAVs and mobile devices.

3) CNN ARCHITECTURES INTEGRATED WITH IoT

With the synergy of DL/CNN models and IoT-driven system, real-time monitoring, and efficient identification of crop pests and disease infestation has been significantly advanced. Among the typical CNN architectures suitable for integration with IoT are MobileNet, EfficientNet, YOLO and SSD which offer lightweight, high accuracy and efficient solutions for processing data on edge devices with limited computational resources. This review revealed a number of studies that employed this integration to achieve remarkable successes in detecting and classifying various pests and diseases affecting agricultural crops. For example, the use of UAV platforms equipped with IoT sensors and embedded with DL algorithms has facilitated proactive monitoring and early detection of crop health issues, with reported accuracies ranging from 91.78% to 99.8% [97], [98]. Additionally, the synergy of mobile device based IoT solutions and DL have enabled farmers to remotely and timely take informed decision about pest and disease outbreaks, empowering them with advanced

TABLE 5. Summary of gaps and opportunity for future works associate with integrating IoT technology with DL/CNN algorithms for Plant Pest and Disease Detection.

Gaps	Effects	Opportunity for future works
Hardware limitations	Limited processing power, camera sensors and memory constraints pose significant challenges for complex DL model deployment	development of light weight and optimized DL/CNN models for resource constraint environment
Less data privacy and security	Possibilities for data breaches and unauthorized access to sensitive agricultural information	Implementing robust security and protection techniques
Limited visibility of certain parts of the plant by camera	Inability to capture potential information from the hidden parts of the plant that hinders the right decision making and leads to incomplete data analysis	development of alternative imaging techniques or multiple cameras deployment for complete coverage of the infected area of the plant
Limited connectivity in rural or remote area	Hindering the seamless and transmission of data between IoT devices, cloud platforms, WSNs and UAVs	Apply edge and fog computing Technologies
Limited datasets	Difficulty in training robust and high accurate models, leading to potential biases and limitations in model performance.	Apply transfer learning, data augmentation, synthetic data generation and active learning technologies
Power consumption constraints	Limited life time and performance of IoT devices in remote area, short performance time for UAVs and increased maintenance activities.	Apply intelligent power management techniques while maintain performance level of the device
Automatic severity detection of infestation	Difficulty in quantifying the infestation level for decision making	Integration of the disease severity estimation algorithms
Constrained detection of various pests and diseases	Inability of detecting various types of pests and diseases affecting plant	Development of multi-purpose DL algorithms to detect different types of pests and diseases simultaneously
Lack of weather and environmental data integration	Hindering of accurate prediction of pest and disease outbreak, leading to inaccurate decision making.	Development of advanced algorithms that integrate weather and environmental data, DL and IoT technology

technological tools for crop management and paving the way for more efficient and sustainable farming practices. Nevertheless, despite these advancements, it is important to acknowledge limitations and challenges associated with security, datasets, hardware, infrastructure and scalability.

B. GAPS AND POTENTIAL OPPORTUNITIES FOR FUTURE WORKS

Despite significant advancement in the state-of-the-art integration of DL/CNN architectures with IoT technology for plant pest and disease detection, this survey uncovered several notable gaps and limitations that require further investigation and research. Table 3 illustrates these gaps and proposes solutions for enhancing performance and improvement for realization of integrating DL and IoT for pest and disease detection.

V. CONCLUSION

This study conducted a comprehensive review of the state-of-the DL/CNN architectures integrated with IoT technology, which have significantly advanced precision agriculture, particularly in the domain of plant pest and disease detection. It focuses on up-to-date CNN architectures and its integration with IoT, revealing existing gaps and possible potential opportunity for future research. The synergy of DL/CNN architectures and IoT-driven systems such as UAVs and embedded devices, has significantly advanced early identification of crop health issues.

Various CNN architectures ranging from early models like AlexNet to state-of-the-art architectures like EfficientNet and YOLO have been developed and applies for specific applications in pest and disease detection, resulting in impressive accuracies, often surpassing 90% and even reaching almost 100% in some instances, such as with GoogLeNet and MobileNet. Furthermore, advancements in object detection architectures such as Faster R-CNN, YOLO, and SSD have enabled precise localization and identification of pests and diseases within crop images, offering efficient solutions essential for proactive crop management and ensuring food security. Additionally, light weight model like MibileNet, EfficientDet and Tiny-YOLOv3 have demonstrated ability to produce small- size and highly efficient models, suitable for resource- constraint environment, such as IoT devices, mobile and embedded devices as well as UAVs for edge application.

Despite remarkable achievement through the integration of the DL/CNN models with IoT devices, such as UAVs and mobile devices, several challenges and limitations remain to be addressed, including hardware constraints, data privacy concerns, limited visibility of certain parts of plant, connectivity issues, dataset scarcity, power consumption constraints, difficulties in severity detection of infestations, and limitations in detecting various pests and diseases simultaneously. To overcome these challenges and unlock the full potential of DL/CNN architectures integrated with IoT, further research and development efforts are needed. These efforts should focus on optimizing lightweight algorithms for accuracy and precision, enhancing security measures, exploring innovative imaging techniques, developing efficient edge computing techniques, optimizing power management, integrating disease severity estimation algorithms, developing multi-purpose DL algorithms, and integrating weather and environmental data. By addressing these areas, researchers and practitioners can advance the field of precision agriculture, improve crop management practices, and contribute to global food security.

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