

CROP DISEASE DETECTION WITH DEEP LEARNING: A SURVEY OF MODERN APPROACHES

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Abstract

Crop disease is a significant challenge to agricultural productivity and food security at a global level. It affects yield at various levels, including manufacturing, storage, and transportation. Pests and viruses account for 50% of total losses in today's world, hence the identification of crop diseases is crucial. Agronomists and specialized infrastructure are needed to overcome these challenges. As demand increases, deep learning (DL) and transfer learning technologies present practical solutions for crop detection. This review highlights recent advances in DL applications that show significant improvements in accuracy and performance through neural networks and transfer learning. Using larger data sets, these models improve efficiency across different types of crops and disease symptoms. The application of these DL models in extracting features and classifying tasks has proven accuracies ranging from 82% to 99.8%. This review also emphasized the importance of publicly available datasets and various open source platforms in ensuring robust testing environments. Two majorly used datasets, Plantville and Plantdoc, are analyzed over different DL architectures, and their Accuracy, Precision, and Recall are mentioned for future use by researchers.

Index Terms—Convolutional Neural Network (CNN), Deep Learning (DL), Transfer Learning, Crop Disease Detection, Edge Computing

I. INTRODUCTION

CROP management integrates diverse practices to control the Crop's environment, pursuing both quantitative and qualitative goals. These complex techniques include crop recognition, quality detection, disease and weed identification, and yield prediction. Crop diseases pose a serious threat to food security; therefore, early disease detection is a crucial and unmet need. In general, agronomist experts conduct field scouting to detect diseases, which is a time consuming process that relies solely on visual inspections. These diseases have a significant impact on global food production systems, adversely affecting crop yields and quality. The effects of crop diseases can vary based on factors such as the severity of the disease, the type of Crop affected, the geographical region, and the management strategies employed by farmers. For instance, a severe outbreak might devastate a specific crop in an area lacking effective disease control measures. This situation could result in financial losses for farmers due to decreased yields, lower market value, and increased expenditures on disease management measures, such as pesticides and fungicides. Infected plants may yield smaller, malformed, or damaged fruits, grains, or vegetables, simultaneously diminishing marketable output. A plant disease, Fusarium Head Blight (FHB), also known as scab, is a fungal disease primarily affecting small grains, such as wheat and barley. Between 1998 and 2000, the total

direct economic losses from FHB in hard red spring wheat, soft red winter wheat, durum wheat, and barley were estimated to be \$870 million [1].

The emergence of deep learning technologies currently employed in this domain enables the precise and efficient detection of crop diseases [2]. The leaf properties, such as color, shape, and the presence of spots, are the leading indicators for assessing the severity of crop diseases. Deep learning techniques for image classification involve facial recognition, object detection, crop disease identification, and handwritten digit recognition [78]. Numerous researchers have explored different datasets, optimizers, and loss functions to improve the accuracy and efficiency of their models in detecting crop and leaf diseases. Deep learning is a multi-step process generally involving data pre-processing and augmentation, training, testing, and data fitting. Recent advancements in deep learning methods, particularly in transfer learning, have yielded promising results for computer vision tasks, including crop disease identification and management. This learning allows models to learn from pretrained networks, reducing time and computational resources. Deep learning has utilized image recognition to revolutionize the diagnosis of plant diseases. The technology identifies visual signals in crop images, including discoloration, pattern irregularities, and morphological changes in leaves and fruits, that indicate health problems. With advanced models finetuned for agricultural use, deep learning enables a noninvasive, scalable, and highly efficient monitoring system. This review examines the application of deep learning in agricultural disease management, focusing on the transition from conventional to technology based methods. This review also explains how these technologies classify and predict diseases and adjust to different crop types and conditions via transfer learning. Crop disease detection is achieved using pre-trained models on large datasets for general tasks, which are being refined to identify specific agricultural diseases. This approach enhances efficiency and minimizes the need for extensive data collection on each new crop disease. The review also discusses real-world applications in agricultural farming, playing an essential role in sophisticated crop management systems. Such systems integrate disease detection with other management strategies, including yield forecasting and quality measurement, to provide a comprehensive solution for agricultural health and productivity.

In summary, deep learning is a revolutionary strategy for plant health management that combines precision, scalability, and flexibility in ways that conventional practices cannot. With further development and research, integrating this cutting-edge technology into crop management strategies promises to provide significant benefits, including improved yield and quality, as well as increased environmental sustainability in agricultural operations. This review highlights the relevance and appropriateness of deep learning technology applications in agriculture, serving as a precursor to future developments that will further redefine the agricultural landscape. The overview consists of eight sections where Section II discusses related work, Section III presents Data augmentation methodology, Section IV presents analysis of datasets with DL methodologies, Section V overviews challenges and open research issues, Section VI presents Gaps in current research and Section VII summarize conclusion.

II. RELATED WORK

Deep learning approaches for disease detection have been studied over the last decade, with an emphasis on creating custom convolutional networks [3]. Transfer learning has become a crucial approach, leveraging the capability of models trained on large datasets to overcome limitations related to the scarcity of labeled farm data. By fine-tuning the models, many researchers have been able to significantly reduce training time and improve model generalization across various crops and diseases. The method not only limits computational cost but also enables models to detect diseases under various environmental conditions and in diverse plant species.

Models such as Mobilenetv2, InceptionNet, Resnet50, AlexNet, DenseNet, and EfficientNet mostly use pre-trained weights. Advanced techniques, such as the Block Attention Module, and well-known networks, including ResNet and VGGNet, aim to enhance the models' ability to focus on essential

features in an image before that region of interest is extracted using Faster R-CNN. For example, Ruihao Dong et al. utilized these modules to direct the model's attention to specific regions of interest, thereby significantly improving the accuracy of disease detection [4]. In the study by Wasswa Shafik et al., an ensemble of different transfer learning architectures for creating PDDnet-LVE achieves an accuracy of up to 97.7% [5]. Segmentation in image processing is another crucial process that utilizes deep learning to identify plant diseases. It is a process of segregating digital images into several segments (collections of pixels or image objects) to simplify and transform the image into a more meaningful and easier-to-analyze form. In plant pathology, segmentation methods are crucial for accurately identifying disease symptoms on plant leaves, stems, or fruits, enabling effective interventions and management strategies. Image segmentation was utilized to detect diseases in various plants, including tomatoes, corn, and wheat. One of the studies by Budsaba Buakum et al. (2024) employed segmentation before CNN learning, achieving 92.37% accuracy [6,7] Whereas Imane Bouacida et al. extract small regions from input images as segmentation and then convolve further for feature extraction.[8] Another research by Divyanshu Tirkey et al. implemented segmentation using YOLOv3 and extracted feature fusion with CNN [9]. Keke Zang et al. compare different transfer learning architectures, with GoogLeNet achieving a better accuracy of 96.51% compared to AlexNet and ResNet [10]. Models such as Mask R-CNN and U-Net are used in semantic segmentation, where each pixel in an image is classified according to the class of the object it represents. The Mask R-CNN model extends Faster R-CNN by adding a new branch to predict segmentation masks for each Region of Interest (RoI) and the existing branch for classification and bounding box regression. Mask R-CNN's accuracy in segmenting infected areas on plant leaves assists in precisely diagnosing the type and severity of plant diseases, achieving accuracies of up to 94.74% for crops such as alfalfa. Similarly, U-Net has also been widely used for agricultural purposes, as it can extract significant features from images. The architecture of U-Net consists of a contracting path to capture the context and a symmetric expanding path that enables accurate localization. Thus, it is explicitly well-suited for segmenting plant diseases. Fig. 1 illustrates various approaches explored by researchers. The architectures of Convolutional Neural Networks (CNNs) have been a key area of recent research, supporting the development of highly advanced methods tailored to the unique visual characteristics of plant diseases. CNNs are optimized for feature extraction from raw images, most effectively detecting vital signs of disease, such as variations in texture, spots, and color. Designing these networks typically involves extensive architectural fine-tuning and hyperparameter optimization to achieve optimal performance on highly specialized tasks, such as detecting subtle symptoms that contribute to early disease progression. Approximately 50% of researchers worked on creating their deep-learning networks. Nasser et al. (2024) developed CTPlantNet for Apple disease detection, utilizing a combination of a CNN and a vision transformer, which achieves an accuracy of 98.28 [11]. Ozbilge et al. (2022) define a CNN as a lightweight, optimized network for classifying tomato diseases [12]. Joshi et al. (2022) detected Rice disease using a custom CNN, a service-based application designed for disease detection using Edge computing [13]. Ten layers of a CNN network were implemented, and a mobile application was deployed on the cloud platform by Ramcharan et al (2019) [14]. Machine learning algorithms, such as support vector machines, k-means, and KNN, are used for prediction and region extraction [15]. It achieves an accuracy of 82%, which is relatively lower than that of deep learning techniques [16]. Patil and Kumar (2022) defined a machine learning approach to process sensory data collected through environmental sensors and input images, which were then passed through a CNN to train the network [17]. A referenced study reports an accuracy of 97.38% for detecting Rice disease. The UAV (Unmanned Aerial Vehicle) was used to collect the dataset in the referenced paper, and subsequently, the model was trained using a CNN for maize disease detection [18].

A. Deep learning Models

Researchers evaluated a variety of architectures, including AlexNet, ZFNet, VGG, GoogLeNet, RCNN, GANs, DeepLab,

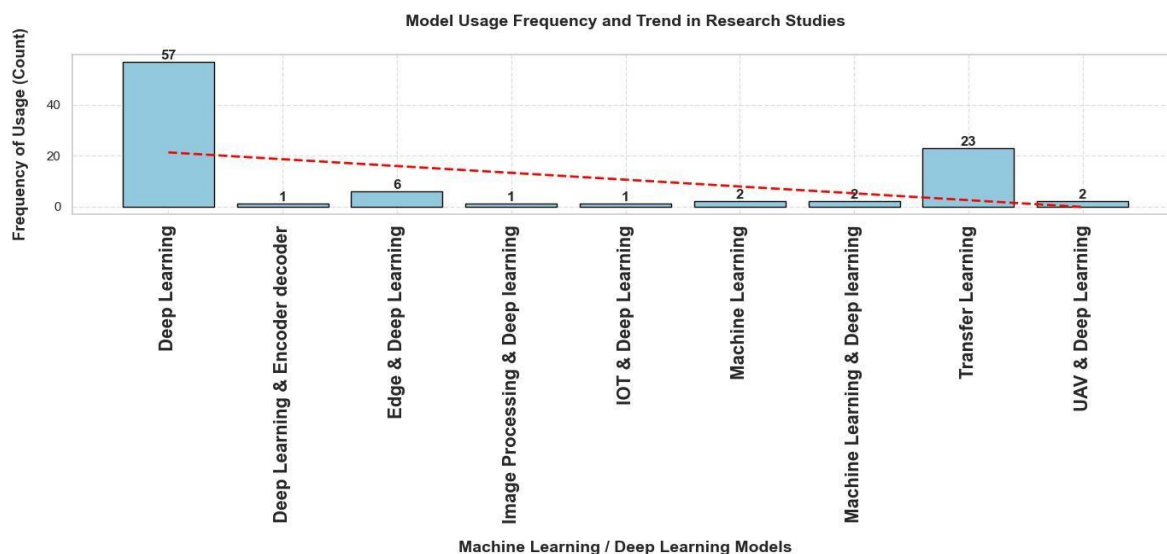


Fig. 1. Comparison of Different Approaches

YOLO, SSD, Faster-RCNN, and DCRN. Models like AlexNet and ZFNet were initially utilized for image recognition using CNN and subsequently adapted for various agricultural applications. Whereas VGG and GoogleNet utilize mainly deeper and more complex features for accurate disease classification. These models have a layered structure, which facilitates the extraction of more complex features from crop images, demonstrating their potential for detecting disease symptoms. With the rise in new trends, models like YOLO and SSD were implemented for the real-time detection of objects by classifying and locating images with a single forward pass. Another method, such as semantic segmentation, is utilized to define the boundaries of symptoms like spots on leaves. The DeepLab used this method to determine disease severity. Similarly, the challenges associated with limited data can be overcome through the use of GANs and transfer learning. GANs are generally used for augmenting datasets and creating custom images that can extend training datasets. Since transfer learning is employed for refining outcomes without collecting data from scratch. By employing pretrained weights from existing data, Faster R-CNN models have been used to achieve accurate results even with smaller datasets [12]. Optimizer and activation functions are used for fine-tuning the models. Several DL models used over the years are depicted in Fig. 2.

B. Optimized Model

Techniques such as mitigating overfitting and underfitting, model checkpointing, learning rate scheduling, and call backs are used to optimize the training model. Optimize model results to achieve nearly the same training and testing accuracy. Optimizers like Adam and ReLU activation functions are used to refine the models and achieve better performance.

C. Visualization

It involves result verification methods and is used to facilitate better understanding, including confusion matrices, ROC curves, feature selection from the first to final layer, Heat maps, and Image segmentation methods [20].

D. Application for Dataset

Mobile application, cloud-based deployed application, or desktop application created based on the trained model. Features given as input and the model predicted binary or multiclass classification. Some of the application provide segmentation.

E. Benchmark Datasets

Comparison and study of widely used crop in Fig. 3. Apple, Grape, Cherry, Corn, Potato, Peach, and Orange crops had major attention for research, whereas Plum, Onion, Cassava, Rice, Tea needs to be focused. Standard datasets, such as Plantvillege and Plantdoc, have been mostly used for study [21-23]. Some datasets are created by merging standard dataset and own images clicked by authors. Fig. 4 shows that most researchers used the PlantVillage and Plantdoc datasets for research. Some applications are composed of a single crop dataset, making them crop-specific. Farmers will assist with a generalized model that consists of a model trained on major crops, along with a geographical Summary of the dataset used for crop disease detection, as shown in Table I. Crop deep, CCMT, Imagery, Tea, and Plantvillege datasets consist of thousands of images, making them more usable than other datasets. Crops and their disease types are labeled to recognize the type of application.

III. DATA AUGMENTATION TECHNIQUE

Data augmentation methods were employed, including a 30% increase and decrease in brightness, contrast, and sharpness. To examine their impacts and increase the dataset's

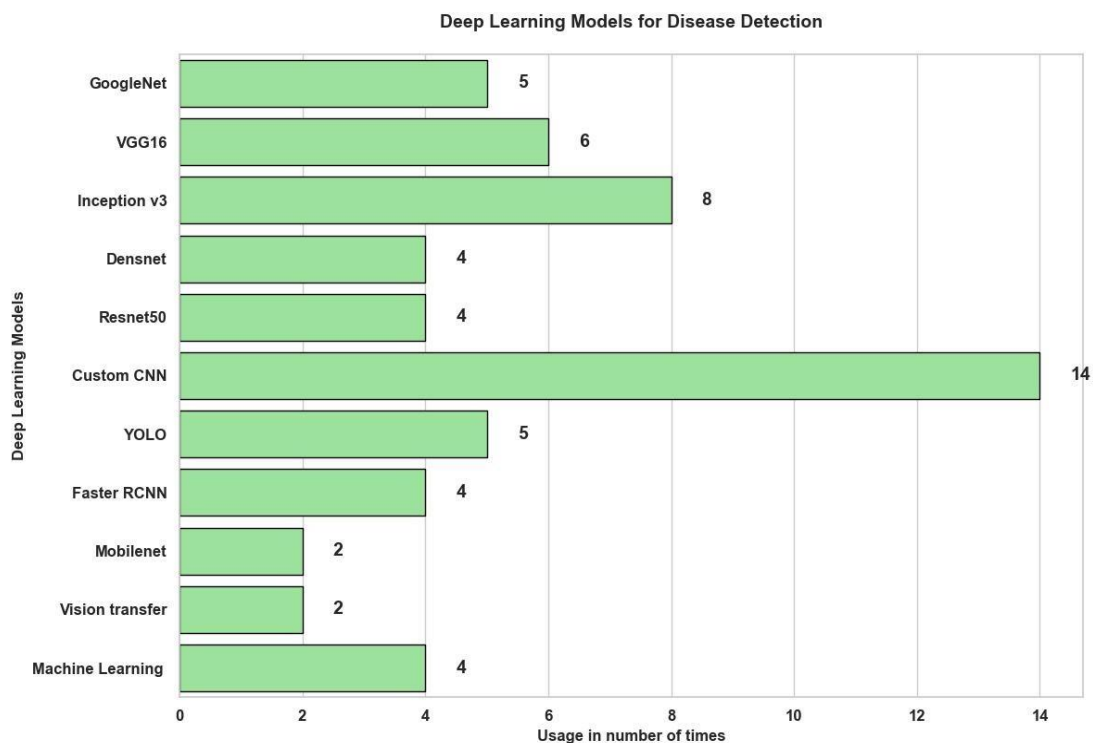


Fig. 2. Several Deep Learning Models have been used over the years

variability, two noises are additionally added to the training images. In this case, the online software program XnViewMP was used to introduce Gaussian and Laplacian noise.40 On a maximum scale of 10.0 and 50.0, the random intensities of 2.0 and 10.0 were chosen, respectively. Additionally, rotational and translational changes, including 90°, -90°, and 180° rotations, as well as horizontal and vertical variations, were considered [57]. Researchers developed an ensemble model by using segmentation and pre-processing methods. To provide a pre-processing and segmentation method for detecting agricultural diseases from leaves utilizing deep convoluted active contour neural network (DCACNN) [58] and convoluted Gaussian filtering. Augmentation steps generally include Scaling, Flipping, Rotation, and adding noise. The authors' cutting-edge method for data Augmentation is referred to as generative adversarial networks (GANs) [59]. GAN seeks to learn the distribution of a training dataset to produce new (synthetic) data instances, unlike any other traditional augmentation algorithms. The discriminator and generator submodels of the GAN model compete with one another. Both actual and false data are used to train the discriminator. The generator learns to produce data

instances that the discriminator cannot distinguish from actual data. CycleGAN is utilized in this case due to its usefulness for picture augmentation among the several forms of GAN suitable for diverse applications.

A. Performance

Evaluation metrics in deep learning are used to assess the performance of models that leverage pre-trained representations from one task (the source domain) to enhance performance on another related task (the target domain). The choice of evaluation metrics depends on the nature of the target task and the specific objectives of the transfer learning experiment [77]. Here are some common evaluation metrics used in transfer learning:

1) Accuracy: The proportion of correctly classified instances in the target task. It is a common metric for classification tasks, providing a measure of the overall model’s performance.

$$\text{Accuracy} = \frac{TP + TN}{P + N} \tag{1}$$

2) Precision: The proportion of correctly classified positive instances (true positives) out of all instances predicted as positive (true positives + false positives). It is useful for imbalanced datasets and tasks where minimizing false positives is crucial.

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

3) Recall (Sensitivity): The proportion of correctly classified positive instances (true positives) out of all actual positive instances (true positives + false negatives). It measures the model’s ability to detect positive instances.

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

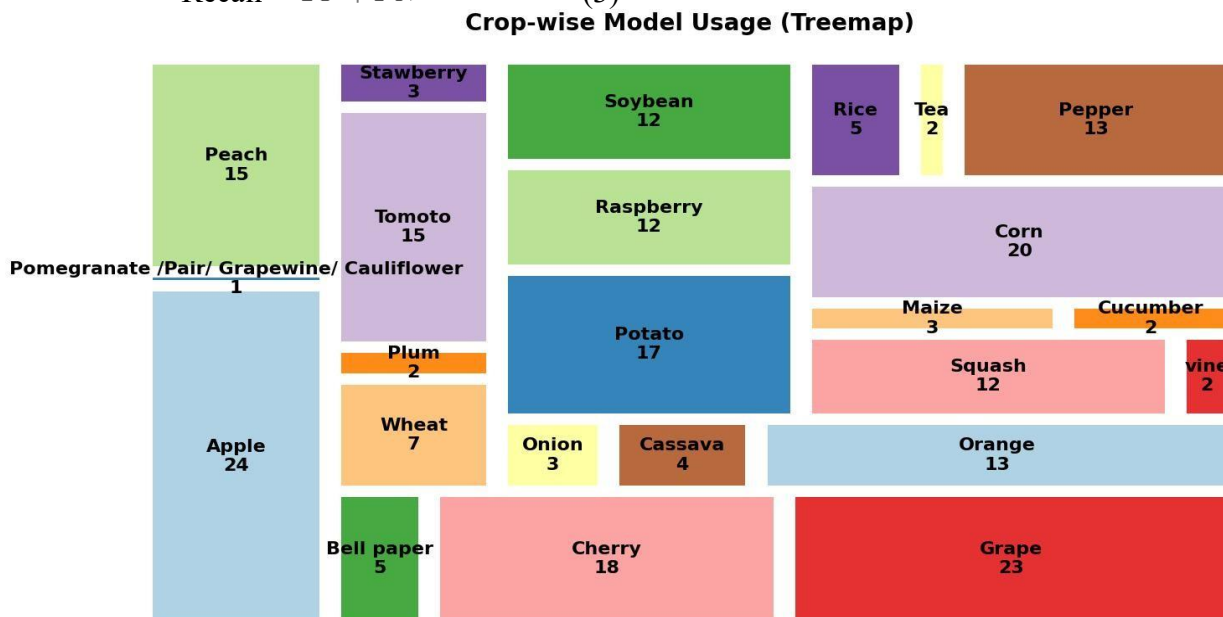


Fig. 3. Widely used crop information

4) F1 Score: The harmonic means of precision and Recall, providing a balance between the two metrics. It is useful when the dataset has imbalanced class distribution.

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

5) Area Under the Receiver Operating Characteristic Curve (AUC-ROC): This metric measures the model’s ability to distinguish between positive and negative instances across various probability thresholds. It is particularly useful for binary classification tasks.

6) *Mean Average Precision (MAP)*: Commonly used for object detection tasks, mAP calculates the average precision at different recall levels. Table VI. Accuracy metrics considered for the comparison and various use cases are referenced along with their limitations and summaries. The fusion model of SVM, KNN, and CNN achieves an accuracy of 99.51%. GAN utilized data augmentation and a transformer for further training of the network, achieving an accuracy of 99.45. Ensemble of transfer learning approaches with segmentation for ROI extraction, achieving an accuracy of 99.8%. Segmentation of ROI extracted using algorithms such as Faster R-CNN. PCA had used with GAN for data augmentation and feature extraction from input images. Inception Net, Google Net, Resnet50, and DenseNet121 perform well and achieve high accuracy for the used dataset under certain conditions. Novel ROI and custom model promise better performance for crop disease detection with all scenario.

IV. ANALYSIS OF DATASETS WITH DEEP LEARNING METHODOLOGIES

Plantvillege and Platdoc are two datasets that have been most commonly used over the decades. Researchers have used custom CNNs and transfer learning approaches, as well as ViT, in recent years. In the analysis study, these two datasets were tested over different deep learning architectures using Google Colab Pro with an NVIDIA Tesla T4, featuring 16 GB of GDDR6 VRAM. The performance of these models is measured across Accuracy, Precision, and Recall — tables V and VI present detailed measures across 20 epochs. Output measures show that Vision Transformer and EfficientNetB4 perform well in crop disease detection. Later, pruning and optimization can be done for Edge AI and mobile device deployment. Data exploratory analysis, Data Augmentation, and detailed training procedures are available at the mentioned GitHub link: <https://github.com/kapil3/Review Crop Disease Detection>. Fig.5 and Fig. 6 show the Plantvillege Dataset accuracy over each epoch and Platdoc Dataset accuracy over each epoch. Model underfitting and overfitting can be understood by examining the loss and accuracy graphs, and adjustments to hyperparameters can be made accordingly. Table VII and VIII presents statistical analysis of both datasets. The statistical evaluation of deep learning models across the PlantVillage and PlantDoc datasets reveals critical insights into model robustness and generalization. Table II,III and IV shows detail performance comparison in recent years with method, accuracy, limitation and summery.

V. CHALLENGES AND OPEN RESEARCH ISSUES

Deep learning has made significant advancements in various fields, but it also comes with its own set of challenges:

A. Large annotated dataset

One of the main challenges in training deep learning models for crop disease management is the scarcity of large annotated datasets. Many small datasets may result in overfitting/underfitting models, which learn well from training data but do not generalize to new, hidden data. This is especially true in agricultural applications where plant species, disease, and environmental variability require large amounts of data to train strong models. Gathering and annotating such big datasets can be costly and time-consuming, particularly for specialized or niche applications [26].

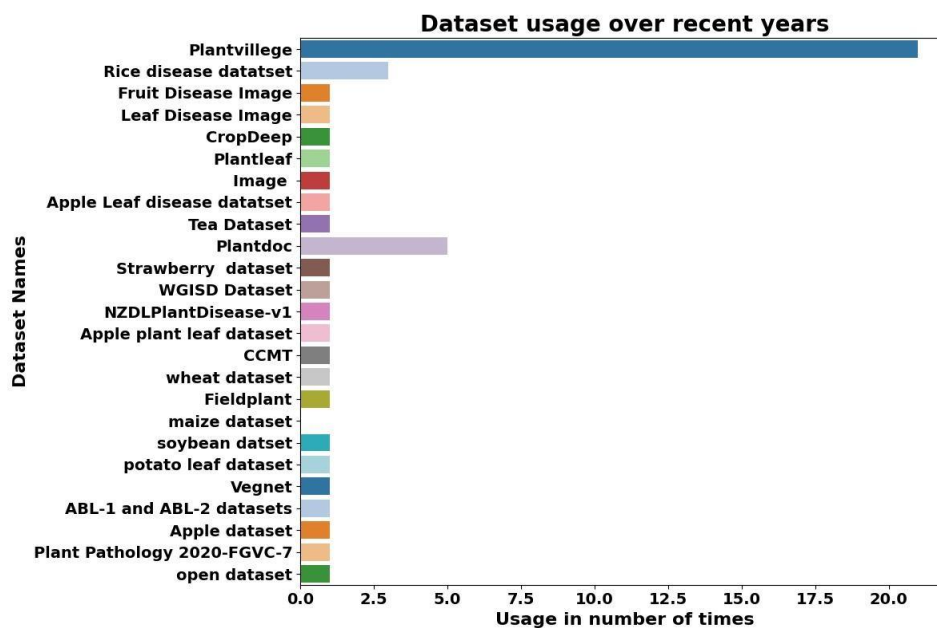


Fig. 4.Dataset usage over recent years

B. Artificial amplification and synthesis of data

Methods such as data amplification, synthesis, and generation are employed to mitigate the issues associated with small datasets. Such advanced techniques include artificially amplifying datasets through image augmentation (e.g., rotation, scaling, cropping) and producing synthetic or artificial images from generative adversarial networks (GANs). However, the issue of Creating synthetic and augmented images that are realistic and accurately reflect real-world scenarios is a significant challenge.

C. Computationally intensive

Training deep learning models can be computationally intensive, particularly for large and complex architectures. Training on GPUs or specialized hardware is standard, but it may still require significant resources, limiting accessibility for some researchers and developers [76].

D. Overfitting

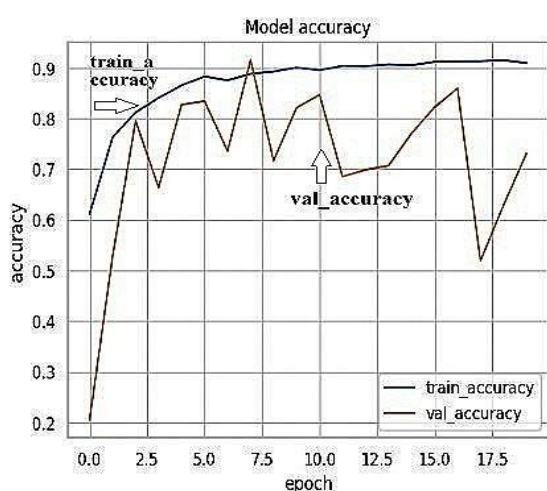
Overfitting is common in deep learning models, particularly when training on minimal datasets. When a model gets overly focused on the training set and cannot effectively generalize to new data, this is known as overfitting. Deep learning models have multiple hyperparameters that need to be tuned to achieve optimal performance. Finding the right combination of hyperparameters can be challenging and time-consuming. Deep learning models are often regarded as "black boxes" because understanding their decision-making process is challenging. Interpreting the learned representations and understanding why the model makes specific predictions is an active area of research [14].

E. Data Bias and Fairness

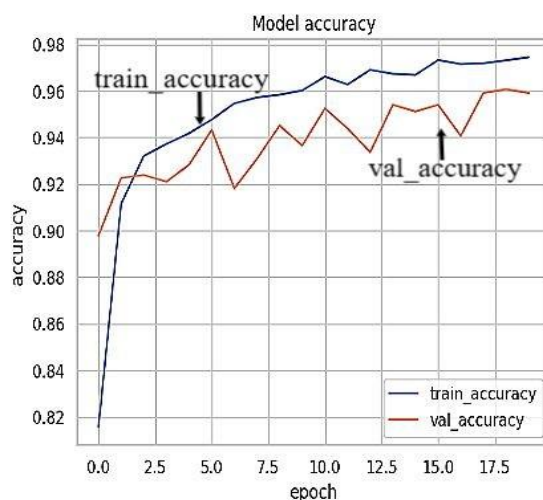
Deep learning models can learn biases inherent in the training data, resulting in biased predictions and unfair outcomes. Ensuring fairness and mitigating biases in model predictions is a critical challenge. Deep learning models lack human-readable explanations for their decisions, making it challenging to justify or trust their outputs in critical applications. Deep learning models are vulnerable to adversarial attacks, where small, imperceptible perturbations to input data can lead to incorrect predictions or misclassification. Reproducing the exact results of deep learning experiments can be challenging due to the models' sensitivity to random initialization and hyperparameter choices [2].

F. Deep learning’s optimization process

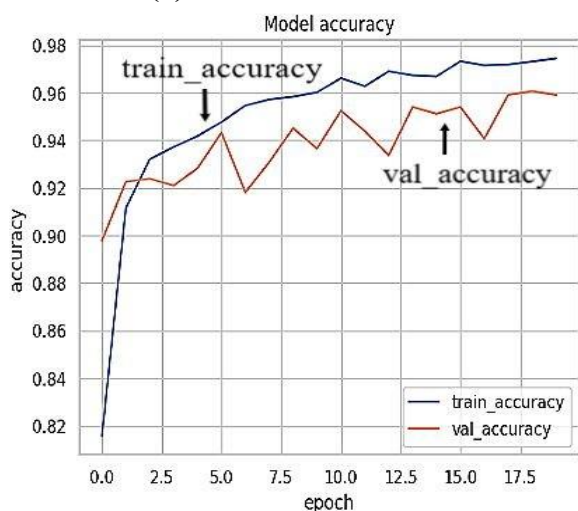
The optimization process of deep learning is complex and not yet fully understood. Researchers continue to explore the learning dynamics and generalization properties of deep networks. Fine-tuning deep learning models and searching for optimal hyperparameters can be time-consuming and require significant computational resources. Addressing these challenges requires ongoing research and collaboration within the deep learning community. Efforts are being made to develop more efficient algorithms, improve data collection and labelling processes, enhance model interpretability, and ensure the ethical and responsible use of deep learning technologies. Despite these challenges, open research remains a vital component in advancing knowledge, promoting collaboration, and fostering transparency in scientific endeavors. Addressing these issues requires collaborative efforts from researchers, institutions, funding agencies, and policymakers to create an environment that encourages and supports open research practices while addressing potential concerns.



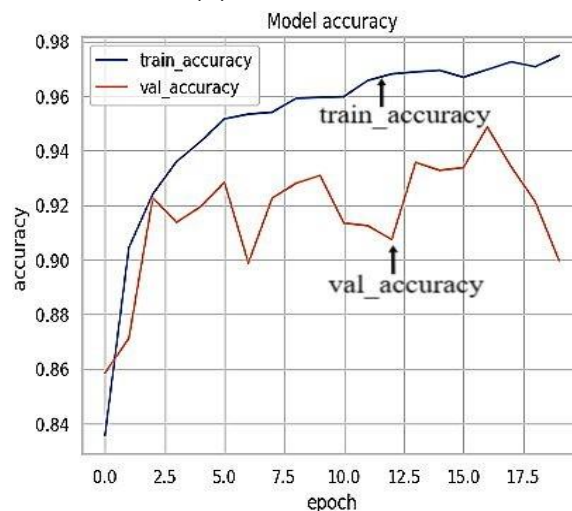
(a) CNN



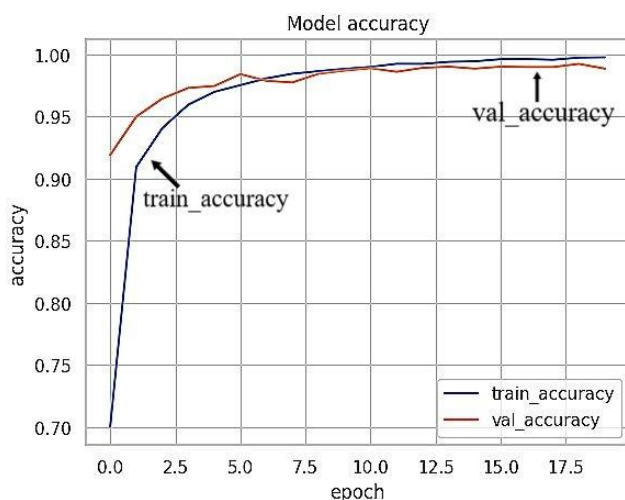
(b) EfficientNetB4



(c) MobileNetV2

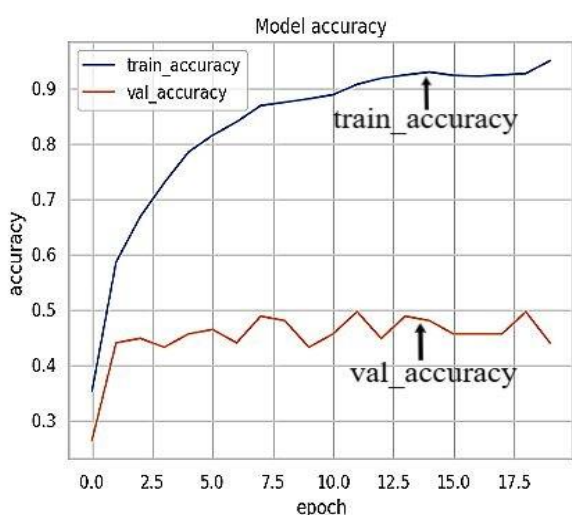


(d) DenseNet201

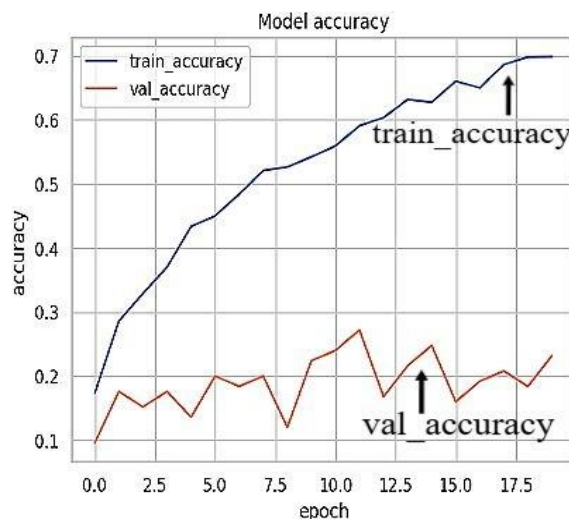


(e) ViT

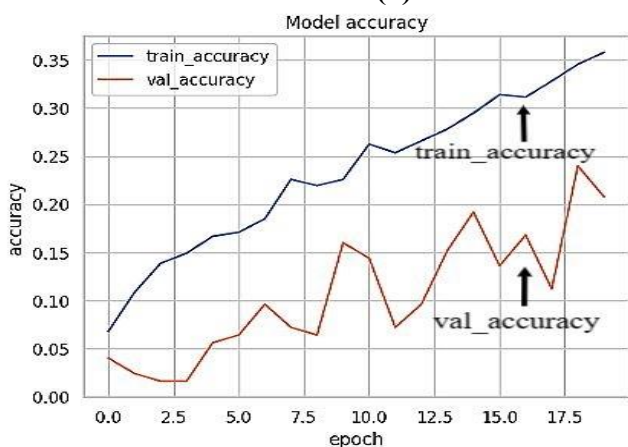
Fig. 5. Plantville Dataset- Accuracy over Epochs (a) Custom CNN (b) EfficientnetB4 (c) MobilenetV2 (d) Densenet201 (e) Vision Transformer



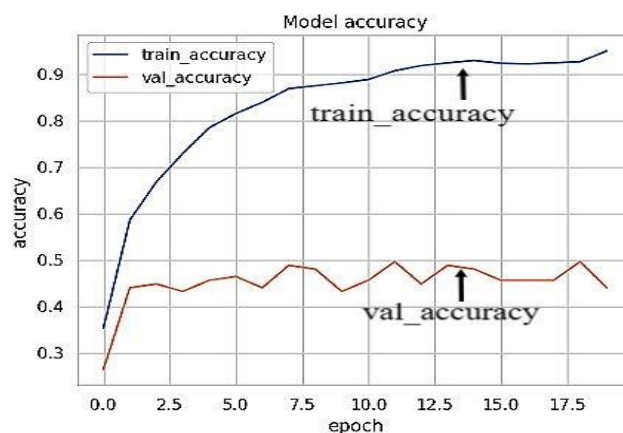
(a) CNN



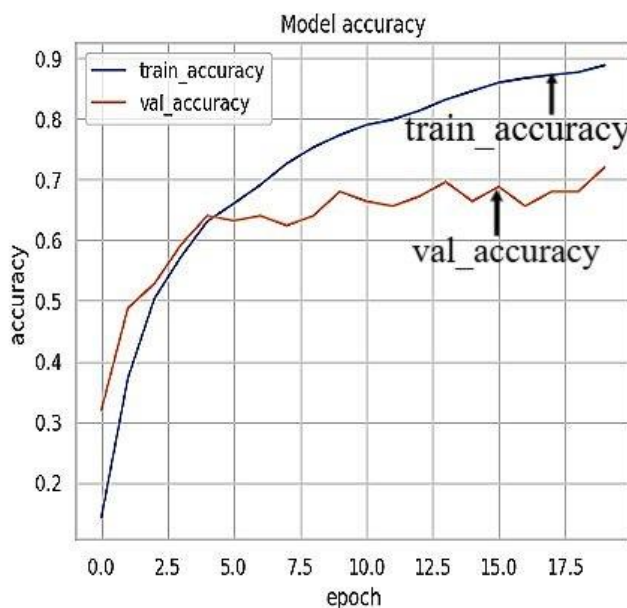
(b) EfficientNetB4



(c) MobileNetV2



(d) DenseNet201



(e) ViT

Fig. 6. Plantdoc Dataset- Accuracy over Epochs (a) Custom CNN (b) EfficientnetB4 (c) MobilenetV2 (d) Densenet201 (e) Vision Transformer

SUMMARY OF DATASETS USED FOR CROP DISEASE DETECTION

Sr. No	Dataset Name	Crops	Disease Classes	Images	Refs.
1	Plant Village dataset	Apple, Blueberry, Cherry, Corn, Grape, Orange, Peach, Bell Pepper, Potato, Raspberry, Soybean, Squash, Strawberry, Tomato	38	87000	[21],[24],[5],[8],[7],[19],[25]–[36]
2	Cassava Disease dataset	Cassava	2	11670	[37]
3	Tomato Disease dataset	Tomato	4	8217	[38]
4	Rice Disease Image Dataset	Rice plants	4	4200	[39],[13],[17]
5	NZDL Plant Disease-v1	Kiwifruit, Apple, Pear, Avocado, Grapevine	3	60–318/class	[40]
6	CCMT Dataset	Cashew,Cassava,Maize, Tomato	22	102976	[41]
7	PlantDoc	Apple, Blueberry, Cherry, Corn, Grape, Orange, Peach, Bell Pepper, Potato, Raspberry, Soybean, Squash, Strawberry, Tomato	13	2598	[42],[43]
8	Apple plant/leaf disease dataset	Apple	4	26377	[44],[45]
9	FieldPlant	Cassava, Corn, Tomato	27	5170	[3]

10	Maize dataset	Maize	5	2107	[46]
11	Wheat Dataset	Wheat	4	1600	[47],[48]
12	Image Dataset	Common Bean, Cassava, Citrus, Coconut tree, Corn, Kale, Cashew Tree, Coffee, Cotton, Grapevines	77	46409	[49]
13	Imagery Dataset	Common Bean, Cassava, Citrus, Coconut tree, Corn, Kale, Cashew Tree, Coffee, Cotton, Grapevines	38	96206	[14]
14	CropDeep	Tomato,Cucumber,Unripe, Squash, Citron, Pawpaw, Head Lettuce, Endive, Butter Lettuce, Rutabaga,Pumpkin,Chili Pepper	31	31147	[50]
15	Tea Dataset	Tea	7	6325	[51],[52]
16	WGSID Dataset	Grape	6	300	[53]
17	Plantleaf Dataset	Apple, Grape, Cherry, Peach, Pepper, Tomato, Potato, Corn	45	3348	[54]
18	Open Dataset	Maize, Paddy	8	7093	[55]
19	AI Challenger pdr2018	Tomato	4	4178	[56]
20	ABL-1 and ABL-2	Centella asiatica	8	14860	[6]
21	Soybean Dataset	Soybean	5	3150	[9]

VI. GAPS IN CURRENT RESEARCH

Current methods struggle to diagnose symptoms of earlystage disease. Environmental conditions affect classification accuracy in wild fields. Existing models may not generalize well across different conditions. A wider variety of training data is needed for better performance. Expansion of the database is necessary for more plant species and diseases. Lack of real-time detection systems in agricultural practices. There is a need for standardized evaluation metrics across studies. Future studies should apply custom neural networks for better optimization. Customized loss functions are recommended for diverse testing datasets. A collection of diverse training data from various geographic areas will help to improve the quality of prediction. Enhancing image quality using robots or autonomous vehicles are recommended. Developing a multilingual mobile application for farmers can be planned using deep learning frameworks, such as TensorFlow Lite. Table IX shows challenges and Future work direction.

VII. CONCLUSION

This review highlights the revolutionary impact of deep learning on crop disease management. State of the art deep learning models were utilized to achieve notable improvements in plant disease identification with impressive accuracy. Findings from various researchers have showcased the ability of deep learning models to surpass traditional image processing techniques, offering enhanced efficiency and reliability in disease detection. Deep learning integrates feature extraction into an end-to-end model, providing significant development opportunities for agricultural applications and crop

disease management. However, practical implications remain challenging due to various factors associated with building accurate models. The natural variation in disease appearance, influenced by lighting and occlusion, emphasizes the need for model robustness and improvements in generalization. Researchers have employed models for real-time

TABLE 1494 PERFORMANCE COMPARISON IN RECENT YEARS

Sr. No	Deep Learning Architecture	Acc. (%)	Ref.	Limitations	Summary
1	ResNet Block Attention Module (CBAM)	& 92.33	[4]	Limited disease classification, data scarcity, annotation challenges	CycleGAN used for synthetic data. Attention added in YOLOv5s, yielding YOLOv5-C3CBAM (12.6 MB, compact for deployment).
2	SVM Darknet	& 99.51	[7]	SVM struggles with large datasets, dependence on transfer learning	Deep learning model (AlexNet + TL). Parameters (epochs, batch size) affect performance. Future: multi-class categorization, nutrient deficiencies.
3	CTPlantNet	98.28	[11]	Data imbalance, generalization issues, high-quality image dependency	Novel "CTPlantNet" architecture for apple disease classification. Integrates preprocessing + CNN/ViT hybrid for symptom detection.
4	YOLO	85	[45]	Data quality dependence, interpretability issues, imbalance, risk of overfitting	CTPlantNet outperformed on Plant Pathology datasets with superior generalization.
5	DDNet-LVE	97.7	[5]	Data scarcity, overfitting, resource needs, background complexity	TL-based model achieved 96.74%–97.79%. Future: real-time multi-object detection.
6	Vision Transformer	99.45	[21]	Class imbalance, augmentation dependence, model complexity	Grad-CAM shows focus on diseased areas. Future: address dataset diversity and sample imbalance.
7	RCNN & MobileNetV3	92.37	[6]	Limited dataset, overfitting, model complexity	Ensemble CNNs + augmentation improved results. Future: TL on larger datasets.
8	GoogLeNet	97.13	[8]	Data imbalance, resource demand, confusion with healthy leaves	Small Inception model for plant disease recognition. Future: improved segmentation methods.
9	YOLOv8-ASFF	87.47	[52]	Imbalance, small-spot detection, symptom distinction errors	One model for multiple crops/diseases. Outperforms specialized methods.

10	YOLOv8	93.2	[60]	Limited diseases, real-time challenges, device compatibility	YOLOv8s tailored for cauliflower disease detection. Annotated dataset + real-time potential.
11	Encoder-Decoder	70.3	[43]	Loss of local information, model complexity, imbalanced class distribution, potential overfitting and underfitting	PL-DINO presents an effective solution for smart agriculture and ecological monitoring. Its performance in leaf disease detection offers opportunities for enhancing agricultural productivity.
12	MobileNet	98.7	[24]	Hardware and software constraints, limited device capabilities, offline functionality, scope of disease detection, dataset limitations	The study identifies a lightweight model suitable for mobile disease identification. Future work will focus on segmentation techniques to assess disease severity. Additional diseases will be included in the app for broader diagnostic capabilities. User-generated images will enhance the dataset, preparing for potential cloud computing options.
13	Inception v3	98.23	[19]	Generalization challenges, dataset limitations, complexity of disease identification, struggles with generalizable models, dependence on background removal and augmentation	The study assessed DL models' generalization for plant disease identification. DenseNet169 achieved the best generalization accuracy of 81.60%. Combining lab and field-acquired images improved model performance. The findings suggest that diverse training data enhances the learning of disease features.
14	Custom CNN	89.29	[23]	Limited contextual information, focus on specific technology, environmental factors, generalization to other plant species, practical implementation challenges, absence of comparative analysis	Protecting plants from diseases is crucial for maintaining healthy gardens and agriculture. Early detection using CNNs enables better management of plant health. Proper treatment methods, including organic solutions, can mitigate disease impact. The web application offers efficient disease prediction compared to manual methods. It holds promise for future use in supporting gardeners and farmers in plant care.
15	Inception & YOLO	98.73	[9]	Real-time insect identification, computational complexity, dataset limitations, lack of	The study demonstrates the effectiveness of deep learning in agriculture. YOLOv5 outperforms other models in speed and accuracy for real-time detection. The

				state-of-the-art techniques, manual annotation requirement, limited crop type coverage	solution can be extended to other crops susceptible to insect infestations.
16	YOLO3	83	[46]	Limited disease classification, data annotation challenges, real-world complexity, dependence on synthetic data, model performance limitations	The YOLOv5-C3CBAM model demonstrated superior detection capabilities for compound diseases in maize. It achieved the highest average precision and recall rates compared to other models, indicating its practical value for real-world applications.
17	SE-VRNet	99.73	[25]	Dependence on dataset quality, generalization to real-world scenarios, complexity of leaf diseases, computational resources, lack of comparative analysis	The model improves accuracy in detecting leaf diseases in real-world scenarios. SE-VRNet is lightweight, making it suitable for mobile applications. The proposed method enhances recognition accuracy and model usability.
18	Xception	96	[47]	Dataset quality and size, class imbalance, model complexity and resource requirements, background noise in images	The proposed system effectively classifies rust into four severity levels. ResNet-50 achieved 96% accuracy with 6 ms prediction time. Future work includes expanding the dataset and improving data collection methods. Drone imagery will be utilized for highresolution data capture in uncontrolled environments. The model will be enhanced to handle variations in illumination and image quality.

PERFORMANCE COMPARISON IN RECENT YEARS

Sr. No	Deep Learning Architecture	Acc. (%)	Ref.	Limitations	Summary
19	PCA DeepNet & Faster RCNN	99.6	[26]	Dataset dependency, generalization issues, model complexity, limited evaluation metrics, potential overfitting	PCA DeepNet improves speed and accuracy, reducing human error in detection. The framework helps farmers minimize losses from pests and diseases. The study establishes PCA DeepNet as a superior method for disease analysis and detection.

20	ResNet	98.98	[27]	Dependence on hand-crafted features, overfitting with small datasets, limited class categories, lack of real-world applications, long training time, vanishing gradient problem	ResNet50 achieved the highest accuracy among the models tested. Future work aims to enhance accuracy with hybrid models and larger datasets.
21	Inception v3	99.9	[28]	Hardware resource constraints, dataset limitations, need for advanced models, quality of image data, economic accessibility	Exploring more powerful deep learning architectures could enhance classification accuracy. Incorporating location and time data may further improve detection reliability. A smartphone-assisted diagnosis system could benefit the agricultural industry.
22	AgriNet	95.64	[42]	Image quality issues, complex background conditions, cost complexity and overfitting, environmental factors, execution time, irregular shape problems	The AgriDet framework improves detection accuracy through advanced techniques. Future work will focus on developing mobile applications for broader accessibility.
23	Custom CNN	98	[61]	Dependence on training data, computational complexity, generalization to other crops, real-time application limitations, lack of extensive performance metrics, potential for misclassification	The proposed deep CNN model effectively identifies apple diseases using leaf images. It assists non-expert farmers and reduces reliance on plant pathologists. Future work includes expanding the dataset for improved model robustness and accuracy.
24	LSTM & CNN	98.91	[62]	Need for extensive training data, complexity of pest identification, technological limitations, generalizability of results, potential for false positives/negatives	The proposed system achieved high accuracy in pest detection using sound analytics. The model's performance metrics include accuracy scores and execution times for various models.
25	CNN with a Complete Concatenated Block	98.14	[30]	Computational complexity, model size and overfitting, generalization across diverse conditions, dependence on dataset quality, limited variants, potential for bias	The Complete Concatenated Deep Learning model (CCDL) is proposed for the detection of multi-crop diseases. The model employs Complete Concatenated Blocks (CCB) for efficient feature extraction and classification.

26	VGG	98.4	[31]	Dataset dependence on image quality, data augmentation constraints, complexity of disease symptoms, performance metrics, scalability issues	limitations, The proposed model achieved high accuracy rates for grapes and tomatoes. Continuous improvement in crop disease classification supports agricultural development. Future work aims to utilize advanced CNN models for deeper crop image analysis. The research encourages farmers to enhance their income and contribute to national growth.
27	Multilayer Perceptron & CNN	96.9	[17]	Insufficient dataset size, limited data augmentation techniques, narrow focus on disease types, challenges in real-time data collection, need for diverse environmental data	The Rice Transformer achieves 96.9% accuracy in classifying rice diseases. The model demonstrates the effectiveness of multimodal fusion and attention techniques.
28	YOLO	95	[63]	Dataset size and diversity, model performance variability, environmental factors, augmentation techniques, dependence on RGB imagery	YOLOv5 demonstrated the best performance for detecting WLD in sugarcane crops. Future research should focus on integrating DL with UAVs for autonomous disease detection. UAV-based DL techniques are currently the most effective for WLD detection in sugarcane.
29	DenseNet	99.81	[32]	Dataset limitations, model complexity and training time, transfer learning dependency, evaluation metrics, lack of real-world testing	DenseNet-121 outperformed other models in classifying plant diseases. The model's reduced complexity makes it suitable for real-time applications. Future work includes developing a mobile application for farmers to identify diseases.
30	ResNet50	96.8	[64]	Implementation cost not discussed, limitations of CNN, data collection and monitoring, focus on specific parameters	Model accuracy is high when training and validation datasets are the same, but it decreases when datasets differ. Data fusion remains a challenge for consistent accuracy. Current algorithms struggle with noisy backgrounds and multiple diseases on a single leaf. Researchers are developing severity-estimation algorithms based on affected leaf area.

31 Deep Convoluted Active Contour Neural Network (DCACNN) 98 [65] Dataset limitations, generalizability, complexity of implementation, dependence on image quality, limited disease types. Addresses plant disease detection with advanced techniques; achieves high accuracy in classifying crop diseases. Future work: expand disease database and enhance training data to improve accuracy.

32 Region-based Fully CNN 93.8 [40] Limited organ consideration, single disease class for some crops, dataset expansion needed, environmental variability, validation limitations. Optimized RFCN achieves high mAP and effectively answers research questions. Future applications include integrating DL methods into automated disease-control systems in agriculture.

Model	Train			Validation			Test		
	Acc.	Prec.	Rec.	Acc.	Prec.	Rec.	Acc.	Prec.	Rec.
Custom Model	90.56	92.19	89.52	73.12	76.02	69.91	75.70	79.02	72.36
EfficientNetB4	97.54	97.65	97.31	95.91	96.05	95.72	95.59	95.64	95.41
MobileNetV2	91.41	92.93	90.17	86.00	88.00	84.51	86.19	87.95	85.39
DenseNet201	97.54	97.81	97.30	89.97	90.59	89.53	90.76	91.54	90.28
ViT	99.80	99.81	99.79	98.86	99.01	98.76	99.03	99.20	98.95

TABLE IV PERFORMANCE COMPARISON IN RECENT YEARS

Sr. No	Deep Learning Architecture	Acc. (%)	Ref.	Limitations	Summary
33	CNN BiCMT	99.23	[66]	Single-modal information insufficiency, unbalanced cross-modal data, complex field environments, dependence on high-quality datasets, further exploration needed	Achieves high accuracy but faces challenges with unbalanced cross-modal data. Future work will address modality insufficiency to improve disease identification robustness.
34	Vision Transformer	96	[67],[68]	Slower attention blocks, heavy network concerns, prediction speed not studied, dataset limitations, image size effects	Compared ViT with CNN and hybrid models for plant disease classification; ViT achieved higher accuracy than CNNs and competitive with literature. Combining attention and convolution improved speed and accuracy. Future work: object localization and multi-label classification systems.
35	GoogleNet	96.6	[53]	Dataset size, dependence on pre-trained models, feature fusion method,	New method for grape variety identification on small datasets. CCA fusion boosts

				computational resources, real-time application challenges	classification and training speed. Future work: collect diverse images for better versatility and build comprehensive software for practical machinery.
36	Mask R-CNN	87.6	[69]	Challenges in real-time processing, dependence on data quality, accuracy limits, implementation complexity, economic/environmental factors	Reported accuracy, precision, recall, and F1. Multilingual mobile app in development; plans to extend to multi-class disease detection.
37	VGG16, means clustering & Faster R-CNN	K- 98.54	[56]	Dataset limitations, single disease detection, generalization issues, dependence on anchor boxes	Future work: collect images in natural environments and consider more plant parts (fruits, stems) for comprehensive tomato disease diagnosis.
38	DCNN	95.73	[58]	Imbalanced training dataset, limited generalizability, dependence on hyperspectral data, lack of external validation	3D CNN successfully identified charcoal rot in soybeans; saliency maps highlighted important wavelengths for classification.
39	MobileNet	99.64	[70]	Insufficient training data, low image resolution, detection failures, generalizability to other crops	Dataset includes complex backgrounds to boost recognition. Future: expand dataset and address low-resolution issues; adapt methodology to other crops.
40	VGG16	95	[71]	Dataset limitations, overfitting concerns, integration challenges, performance metrics	95% accuracy for mildew in millet. Future: expand to other crops and integrate into farmerfacing digital devices.
41	ResNet50	93	[72]	Limited expressive power of classical methods, real-world deployment challenges, dataset limitations, acquisition complexity, bias-variance trade-off	Crop-conditional CNN with contextual metadata; multi-crop model outperformed single-crop models. Future: larger datasets and studying multiplicative suppression topologies.
42	Inception v3	99.75	[73]	Overfitting, insufficient samples, annotation quality, disease complexity, operational challenges	Many CNN solutions are not yet operational due to ML practice gaps. Results are promising for tools supporting sustainable food production.

43	Faster R-CNN	95.48	[74]	Dataset size, parameter sensitivity, symptom complexity, compute cost, potential human error	Updated Faster R-CNN detects diseased sugar beet areas with 95.48% accuracy; recommends larger datasets/algorithms and better image quality for improved performance; supports real-time intervention.
44	VGG16	99.53	[75]	Database limits, test-set concerns, real-condition image gaps, misclassification risk, computational limits	Specialized CNNs achieved 99.53% on unseen images. Real-condition images are vital; low compute enables mobile apps. Future: expand databases, diversify data, and improve robustness across sources.
45	Recurrent Neural Network	84.9	[48]	Imbalanced dataset, dependence on feature reduction, generalization, preprocessing limits, model complexity	Robustness and generalizability are key for large-scale detection. Deep models beat SVM; hybrid 2D-CNN-BidGRU showed best robustness/generalization.

TABLE V ANALYSIS OF PLANTVILLAGE DATASET OVER DEEP LEARNING METHODOLOGIES

TABLE VI ANALYSIS OF PLANTDOC DATASET OVER DEEP LEARNING METHODOLOGIES

Model	Train			Validation			Test		
	Acc.	Prec.	Rec.	Acc.	Prec.	Rec.	Acc.	Prec.	Rec.
Custom Model	34.51	63.63	12.34	20.80	33.33	6.00	12.26	43.32	8.00
EfficientNetB4	95.05	96.20	93.72	44.00	50.48	42.40	48.45	52.26	44.48
MobileNetV2	64.56	84.30	47.92	28.00	37.66	23.20	28.10	35.92	22.77
DenseNet201	69.18	84.70	53.29	23.20	32.20	15.20	17.29	21.14	11.35
ViT	88.50	92.25	81.17	72.00	81.82	64.80	79.34	85.44	74.67

TABLE VII STATISTICAL ANALYSIS OF PLANTVILLAGE DATASET RESULTS

Model	Mean (%)	Std. Dev. (%)	Min (%)	Max (%)	Rank
ViT	99.38	0.35	98.76	99.81	1
EfficientNetB4	96.93	0.70	95.41	97.65	2
DenseNet201	93.15	3.00	89.53	97.81	3
MobileNetV2	88.73	2.80	84.51	92.93	4
Custom Model	82.04	7.40	69.91	92.19	5

TABLE VIII STATISTICAL ANALYSIS OF PLANTDOC DATASET RESULTS

Model	Mean (%)	Std. Dev.	Min (%)	Max (%)	Rank
ViT	80.66	8.85	64.80	92.25	1
EfficientNetB4	62.62	23.39	42.40	96.20	2
MobileNetV2	41.50	20.89	22.77	84.30	3

DenseNet201	36.63	25.10	11.35	84.70	4
Custom Model	26.46	18.07	6.00	63.63	5

TABLE IX CHALLENGES AND FUTURE WORK

Observed Gap / Challenge	Research Direction / Future Work
Limited real-field datasets (most studies rely on PlantVillage)	Build and share region-specific datasets; apply Generative AI augmentation (Diffusion, GANs) to enrich rare diseases.
Class imbalance (some diseases with very few images)	Employ synthetic data generation and balancing; use class-aware augmentation and few-shot learning.
CNN-based methods achieve high accuracy but fail in real-world noisy conditions	Explore Transformers and Hybrid CNN-ViT models; evaluate under robustness benchmarks (noise, blur, brightness).
Heavy ViT and EfficientNet models unsuitable for farmer devices	Design lightweight models (MobileNet, EfficientNet-lite, quantized TFLite, pruning, NAS) optimized for Edge-AI.
Lack of explainability (farmers/researchers don't trust blackbox predictions)	Incorporate XAI techniques (Grad-CAM, SHAP, LIME) for interpretable disease diagnosis.
Most surveys compare accuracy only, ignoring efficiency	Compare accuracy, latency, model size, FLOPs, energy use for real deployment relevance.
Few works integrate advisory/remedy systems	Combine detection models with local-language advisory and decision support systems.
Limited use of multimodal signals (image-only focus)	Integrate leaf images + farmer voice + text descriptions (multimodal GenAI).
Rare disease classes underrepresented in literature	Apply few-shot, meta-learning, transfer learning, diffusion augmentation.
Weak benchmarking and reproducibility	Encourage open-source code/dataset releases, standardized train-test splits, and reproducibility protocols.

disease diagnosis through transfer learning methodologies. Instead of creating a specific local dataset focused on crops, many researchers have utilized well established datasets and expanded existing or public datasets by adding high-quality images. The comparative evaluation of ViT, EfficientNetB4, MobileNetV2, DenseNet201, and a Custom CNN model across the PlantVillage and PlantDoc datasets highlights the critical gap between controlled and real world conditions. On the PlantVillage dataset, all models exhibited strong performance, with ViT achieving the highest accuracy (99.38%) and demonstrating remarkable stability, followed closely by EfficientNetB4 and DenseNet201. However, when tested on the more challenging PlantDoc dataset, performance dropped significantly, where ViT again emerged as the best performer (80.66%) but with higher variability, while EfficientNetB4 maintained a competitive position. In contrast, MobileNetV2, DenseNet201, and the Custom model suffered considerable degradation, reflecting their limited robustness in field-based scenarios. These findings emphasize the importance of not only optimizing models for benchmark datasets but also validating them under real-world conditions to ensure reliability in practical agricultural applications. Crop disease diagnosis can be effectively achieved by leveraging edge AI computing alongside thermal imaging sensors, a newly generated dataset, a geographically focused dataset, and a multimodal learning technique. Thus, future research directions for this review include

enhancing the accuracy of disease localization on plant leaves through the development of hybrid deep learning models. This approach would further enhance the accuracy of disease identification and improve the effectiveness of disease control systems. Additionally, incorporating a larger dataset to cover multiple leaf diseases would help the model generalize better across different crops and conditions. Current research suggests that integrating deep learning into crop disease management systems has significant potential for facilitating early disease detection and precise severity estimation. This integration could enhance the efficiency of agricultural practices and promote sustainable farming methods by reducing reliance on chemical treatments and enabling timely interventions.

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