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Intelligent Leaf Disease Detection Using Deep Learning: Trends, Challenges, and Innovations

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Abstract: Timely detection and classification of plant diseases are essential for effective crop management and ensuring food security. Recent advances in deep learning, particularly Convolutional Neural Networks (CNNs), have enabled automated disease diagnosis using leaf images with high accuracy. This paper reviews research from the past five years, covering model architectures, feature extraction methods, datasets, data augmentation techniques, and evaluation metrics used for disease classification across various crops.

Although these approaches perform well in controlled environments, challenges such as varying lighting conditions, complex backgrounds, and poor image quality limit their real-world applicability. Existing systems also lack disease severity estimation and struggle with generalization across diverse crops. Future research directions include multi-crop disease classification, real-time deployment on smart devices, and improving model interpretability for practical agricultural use.

Keywords: Datasets, Convolutional Neural Networks, Deep Learning, Machine Learning, Plant Disease Detection

I. INTRODUCTION

Karnataka holds the 5th position in India in terms of total area in vegetable crop production.. Agriculture plays a vital role in Karnataka's economy, with the state being a major producer of various crops including rice, ragi, coffee, jowar, maize, pulses, sugarcane, cardamom, chillies, arecanut and coconut etc.

Consequently, on the other hand crop diseases pose a significant and on-going threat to the agricultural sector by reducing crop quantity and quality. Further to control these diseases, pesticidal, fungicidal or chemical remedial measures needs to be taken. This causes lot of damage to the health of living beings, harm to the environment and biodiversity loss. Therefore, to stop further damage it is very important to identify crop diseases in early stage and classify them accurately.

In traditional disease detection approaches, farmers or professionals perform visual inspections. Microscopy, laboratory testing and consultation with plant pathologists are all examples of classical procedures. Despite their benefits, these procedures are time-consuming, necessitate laboratory use, require competence and are not appropriate for large farms.

To overcome these obstacles, researchers are increasingly turning to technology-based solutions particularly in the areas of computer vision and machine learning to automatically identify plant diseases from images. One of the most promising approaches in this sector is the use of deep learning models, specifically Convolutional Neural Networks (CNNs) [1] , in image recognition and classification tasks, which have proven to be quite effective.

Research investigations for the detection of plant diseases often use leaf pictures because they provide the most accessible and aesthetically pleasing source of information. Disease symptoms such as discolouration, stains, lesions, or wilting, frequently begin on the leaves, making them reliable indicator of the plant's health. Large datasets of leaf pictures have also led academics to focus on leaf-based detection, which allows for standard evaluation and comparison of multiple models.

Although deep learning models are constantly improving at diagnosing plant diseases, there are still a number of obstacles to their successful deployment. Researchers face two significant challenges while training the model: a lack of dataset diversity and quality. Plant Village and other existing datasets frequently produce high-quality results in controlled situations[2]. Field photography frequently features inconsistencies such as murky lighting and a complex background. As a result of these real-world issues, model accuracy suffers significantly, especially when the systems were trained on clear, high-quality images. In fact, field photos frequently have difficulties such as shadows, overlapping leaves, and uneven leaf structures, complicating correct classification.

Most existing models designed to distinguish between healthy and sick leaves and do not address the necessity for severity estimation[3]. But to decide how much insecticide to apply and to determine which crops requires immediate treatment severity detection is required. Even though few recent techniques have tried to find out the severity of disease, many models still have trouble producing accurate results in this area.

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This paper provides a comprehensive survey of more than 15 papers in the field of plant disease detection using leaf images. The paper also discusses the datasets used, with a focus on those that are publicly available and commonly used in plant disease detection research. We aim to highlight the strengths and limitations of these approaches, identify the challenges faced in real-world deployment[4], and outline the future directions in this area, such as the integration of disease severity estimation, and the expansion to multi-crop disease classification.

The ultimate goal is to improve the practical applicability of plant disease detection systems, enabling farmers, especially in remote and resource-limited areas, to leverage technology for more effective crop management and disease prevention.

II. BACKGROUND

A. Overview of Datasets, Crop Coverage, and Computational Tools in Reviewed Studies

1) Disease Datasets used in the reviewed papers.

Many datasets were utilized in the research papers to train, evaluate and analyse the proposed methods and algorithms. These datasets provide diverse and comprehensive data for testing the model's performance across different tasks. Datasets like Plant Village Dataset, Mangopes, Cotton Disease Dataset, BananaLSD, Apple Leaf9, Cucumber Leaf Dataset, IBean Dataset, Soybean Leaf Dataset, FGVC7, Mendeley Dataset, PigeonPea Leaf Image(PPLID), Groundnut Leaf Disease Dataset, Agricultural, Paddy Doctor Dataset, Rice Leaf Dataset, AI Challenger 2018, Tomato leaf disease Dataset, Wheat Disease Five Classes Classification Dataset (WD5CC), and Custom dataset collected from field.

2) Crops which are considered for Disease Detection

In this survey the following crops from different varieties as in the figure 1 are considered for disease detection and classification. In food crops rice, wheat, maize, millets and pulses are considered. Commercial crops are very important to generate economy for our country. So, crops like cotton, sugarcane and groundnut are taken into the consideration by researchers. In Plantation crops tea and coffee and in vegetables Cassava], Tomato, Potato, Beans and Chilli are considered. In fruits, Grapes, Citrus, Mango and Apple are taken. And finally in spices pepper and cardamom are taken into account.

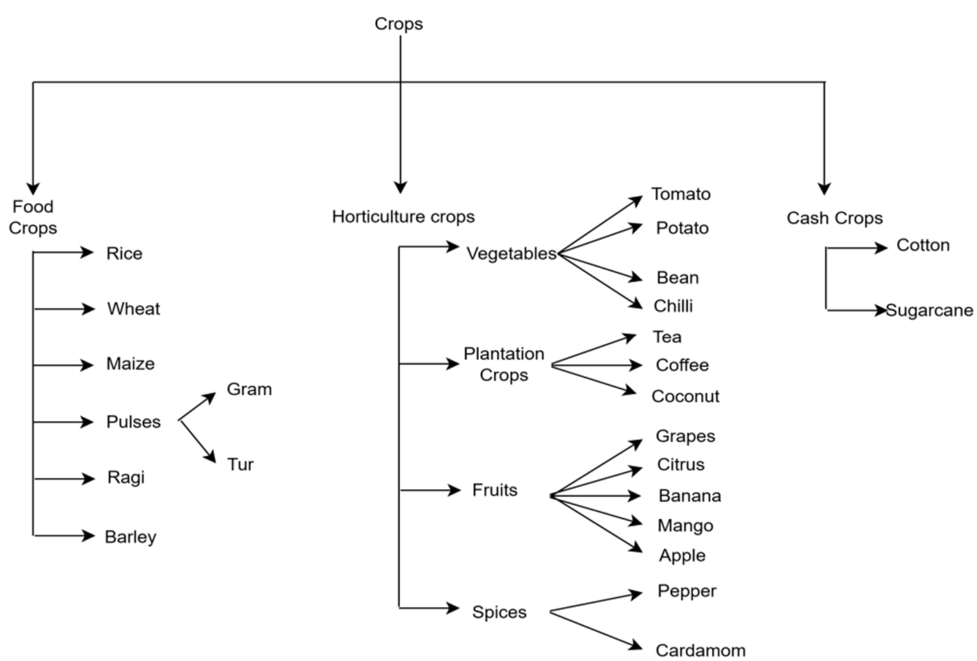

Figure 1: Major Crops which are considered for disease detection

3) Tools and Frameworks used

The setup uses **PyTorch 2.0**, **TensorFlow, Keras**, and **Scikit-learn** for model development and machine learning tasks, with **Python 2.7** and **2.8** for compatibility. Running on **Windows 11**, it leverages **CUDA 12.1** and an **RTX A2000 GPU** for accelerated computation, enabling efficient crop disease detection and classification.

B. Steps for Crop Disease Detection and Classification:

Below Figure 2 shows the different steps involved starting from data collection to disease detection and classification.

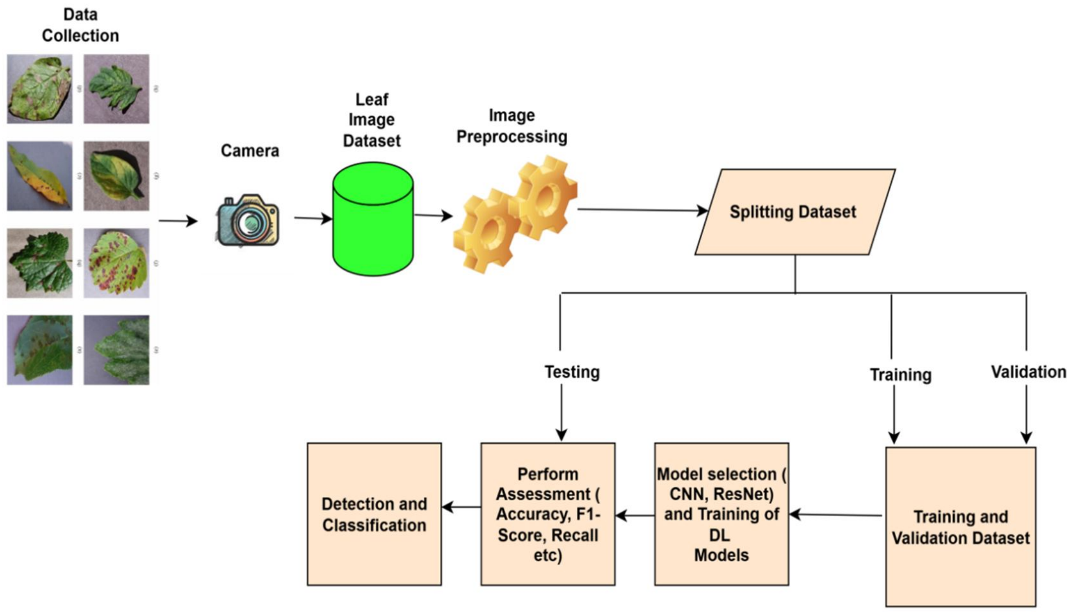

Figure 2: Disease detection and classification steps

1) Data Collection

Images of crops: Collect the images of healthy and diseased crops either from publicly available datasets, or one could create a custom dataset by capturing crop images in the field.

2) Data Pre-processing

Resizing: Resize the crop images to a fixed size (e.g., 224x224 pixels) to ensure compatibility with the deep learning model input.
Normalization: Normalize pixel values to make training more efficient.
Data Augmentation: Since deep learning models require large datasets for good generalization, this helps to simulate a variety of conditions for each image. This can include rotation, flipping, zooming shearing and brightness adjustment.

3) Train/Test Split

Split the dataset into training and testing sets, typically in an 80/20 or 70/30 ratio.
Training Set: Used to train the model.
Test Set: Used to evaluate the performance of the model on unseen data.

4) Model Selection

Convolutional Neural Networks (CNNs): Most commonly used models for image classification tasks.
Pre-trained models: Models like ResNet, VGG16, or Inception can be fine-tuned on the crop disease dataset if computational resources are limited.
Custom Architecture: A custom CNN could be designed, but this requires more training data and tuning.

5) Model Training

Loss Function: A loss function like categorical cross-entropy for multi-class classification is typically used.
Optimization Algorithm: Use algorithms like Adam or SGD (Stochastic Gradient Descent) for gradient optimization.
Epochs: Train the model for a certain number of epochs. The training process adjusts the weights of the network to minimize the loss function.

6) Evaluation

Evaluate the model using test dataset once it is trained.
Key metrics include: Accuracy, Precision, Recall, F1-Score and Confusion Matrix.

7) Inference (Prediction)

Deploy the Model: Once trained, the model can be deployed to classify new crop images as either healthy or diseased.
For disease detection, the model can output labels such as "Healthy", "Leaf Blight", "Powdery Mildew", etc., depending on the types of diseases in the dataset.

III. RELATED LITERATURE

This study presents different DL methods and customised models applied for leaf disease detection and classification. Also this review tells in how many papers severity detection is done, light weight models are developed, hyper spectral images considered etc.

A. Goal and Research Question

The main goal of this survey is to review the latest literature and to reveal research gaps and challenges. This information is required for the researcher if he/she is working on plant leaf detection and classification. After this survey the main plan is to answer the research questions: Which machine and deep learning algorithms have been used to detect and classify leaf diseases, which method gives better accuracy results, which model is suitable for mobile deployment and which model detects severity of the disease?

B. Data Extraction

In our study we considered recent papers published between 2020 and 2025. Below Figure 3 shows that the Maximum papers are published on this work during 2024 and 2025 on various crops. These papers include both ML and DL methods for finding leaf disease and classification. We organised the papers in different folders year wise for easy access.

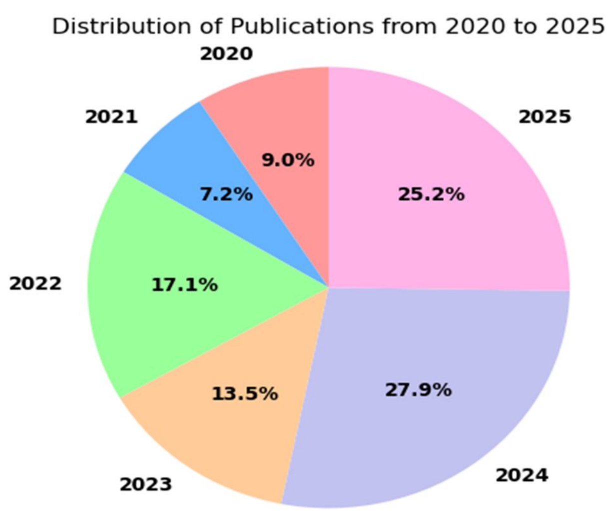

Figure 3: Number of papers considered to our study year wise from 2020 to 2025

IV. RESULTS

In this section we discuss different studies that contributed to the answer to our research questions.

1) Which Machine/Deep Learning Algorithms Have Been Used To Detect Leaf Diseases?

Based on our findings studied from different research papers, we found that Convolutional Neural Networks (CNN), support vector machines (SVM) and Deep Neural Networks (DNN) algorithms are used. We realized that a Convolutional Neural Network (CNN) is a widely used algorithm. Around 85% researchers interested in deep learning. There were around 6% of machine learning algorithms used in the papers. In 10% papers, machine/deep learning algorithms and traditional algorithms combined. Table 1 shows the information of this.

Table 1.Percentage of Machine Learning/ Deep Learning algorithms used.

Type of algorithm	Percentage
Deep Learning	85%
Machine Learning	6%
Traditional Algorithms	3%
Combination of ML and DL	6%

2) Which Deep Learning Architectures used?

Here we can find different Deep Learning architectures used in the papers reviewed by us. As we can see in Figure 5 % here 23% of the researchers have used ResNet,16% VGGNet, 15% MobileNet, 12% YoLoV8, 11% EfficientNet , 8% DenseNet and 25% others.

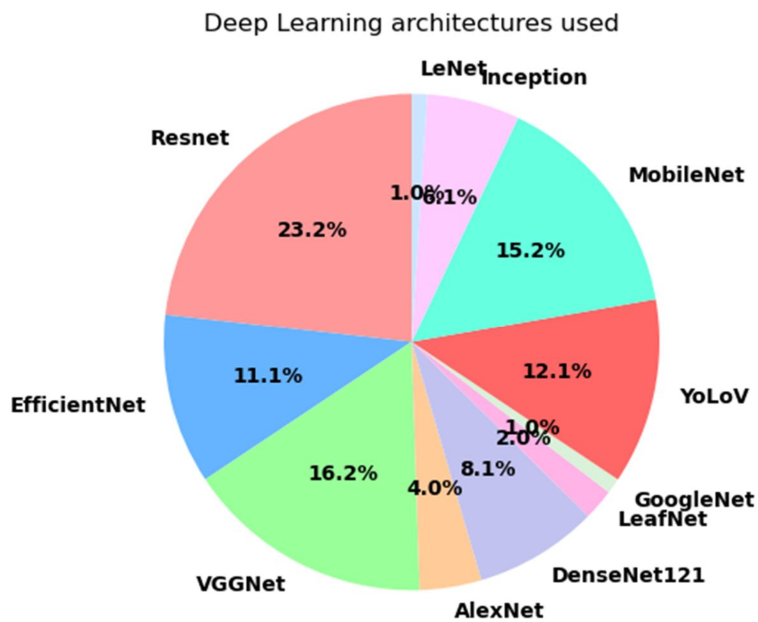

Figure 4: Deep Learning architectures used in the reviewed papers.

3) Which models have been used to find out the severity along with the disease detection?

The table2 highlights recent deep learning models for plant disease detection and severity estimation across crops like coconut, tomato, ash tree, and corn. As shown in the Figure 6 models such as DenseNet121, ResNetV2, and YOLOv5 show high classification accuracy, with some also addressing disease severity. While, these models perform well on datasets like PlantVillage and synthetic data, most face challenges related to real-world testing, lighting variations, and limited disease classes. Some models, like Faster R-CNN for corn, demonstrate robustness in varied field conditions but require optimization for mobile deployment. Overall, there is a need to improve generalization, handle complex field scenarios, and support real-time applications.

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Table 2: Papers on severity detection

SL NO	Refe renc e	Method	Crop	Dataset used/im agescou nt	Accurac y Achieve d	Advantages	Drawbacks
1.	[5]	Custom CNN Model	Tomato, Potato, Apple and Grape	Plant Village Data Set/540 00	92.06%	Combines classification and severity Estimation	1. Misinterpretation of severity estimation sometimes due to lighting issues. 2. Not tested on noisy real-world field datasets

2.	[6]	YOLOv5	Ash Tree	Synthetic Dataset/ 15,000	96.3%	Considered Real data.	1.Limited real-world test data 2. Misclassifications between early and mid-stage infections.
3.	[7]	A custom Faster R-CNN	Corn	Plant Village Dataset/ 2112	97.89%	Classification of disease spots in real-world field conditions with varied lightning, clutter, weed, soil etc.	1. Not a lightweight model. 2. Model works on single-label and single class detection 3. Model trained and tested on small dataset. 4. False detections in early disease stages or under extreme lighting

The table 2 presents a comparison of different deep learning approaches for crop disease severity detection across various crops. Models such as Custom CNN, YOLOv5, and Faster R-CNN achieve high accuracy ranging from 92% to 97.89%, highlighting their effectiveness. While these methods offer advantages like combined classification and severity estimation and adaptability to real-world conditions, they also face limitations such as sensitivity to lighting, limited real-world datasets, and difficulty in early-stage detection. Additionally, some models are computationally complex and not lightweight. Overall, the study indicates a need for more robust, generalized, and field-deployable solutions.

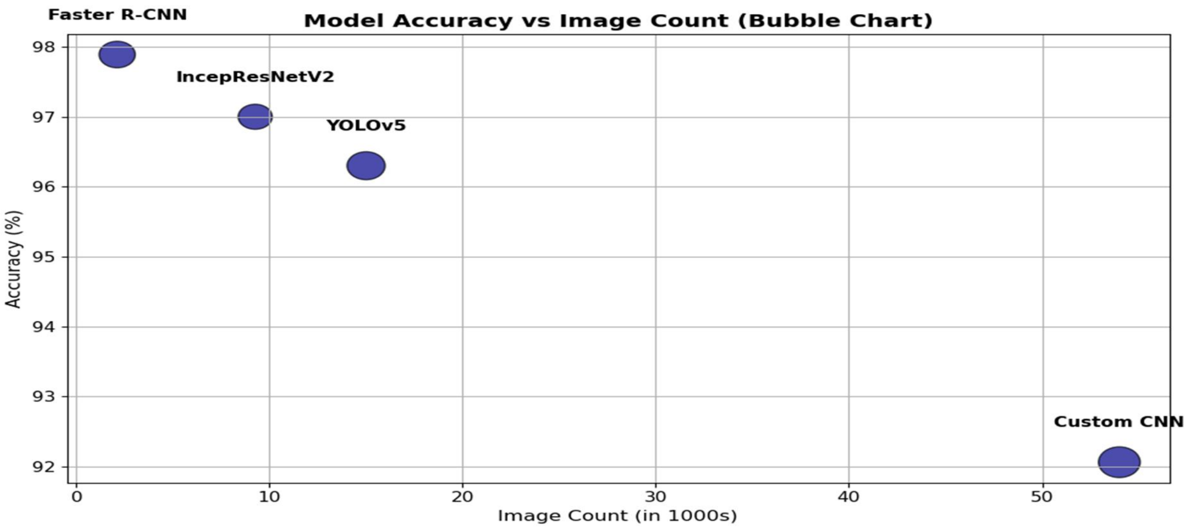

Figure 5: Accuracy obtained by methods over Dataset of different size

4) How many Light- weight models are developed for Mobile Deployment?

Table 3: List of Lightweight Models Developed

SL NO	Method	Crop	Dataset used	Accuracy Achieved	Advantages	Drawbacks
1.	Mobile NetV2	Maize	Maize Disease Dataset	97.44%	Light weight model, Less number of parameters	1. Model is not tested on real world noisy farm images. 2. Severity classification not performed
2.	Custom CNN	Coffee	BRACOl	97.77%	Lightweight model with 3 layers	1.No severity estimation 2. no real-world deployment

3.	MobileNetV3	Tomato	PlantVillage Tomato Leaf Disease Dataset	98.77%	Created for Android with the ability to identify multiple diseases	1. When tested on real images accuracy falls to 95% 2. Severity estimation is not incorporated 3. Focused only on Tomato images.
4.	Improved MobileNetV3 based TDR Model	Tomato	Tomato leaf dataset from Kaggle	96%	Designed to process foggy images using Improved DCP dehazing algorithm for image clarity and ODC for more effective feature extraction.	1.Model lacks training on real images 2.Model testing only on small datasets and on single crop. 3. Severity estimation is not incorporated
5.	Improved YOLO v8	Grape	Self-built dataset	93%	Computational cost is less, less number of parameters taken so suitable for mobile deployment.	1.Dataset with less disease classes and of high quality . 2.only one crop was taken 3. Model is not tested on images under varying lighting 4. Severity estimation is not incorporated
6.	Modified Mobile NetV3 small CNN Model	Mulberry	Collect locally in filed.	96.4%	Real data is considered and the model is lightweight.	1.Limited disease types are taken. 2.Misinterpretation of 2 diseases leaf spot and rust. 3.Real –time farm monitoring is lagging 4.Lack of model generalizability. 5. Severity estimation is not incorporated
7.	YOLO V8	Citrus	Collect locally in filed.	92.6%	Very lightweight and filed data is used	1.False positives possible under complex lighting 2.No real-time validation is done

The table 3 summarizes multiple deep learning models used for crop disease detection and severity analysis across crops like maize, coffee, tomato, corn, and ash tree. Models such as MobileNetV2, MobileNetV3, YOLOv5, Faster R-CNN, and custom CNN achieve high accuracies ranging from around 92% to 98%, with many focusing on lightweight design and efficient feature extraction. Some approaches also incorporate image enhancement techniques like dehazing to improve performance. However, common limitations include lack of real-world validation, reliance on small or synthetic datasets, absence of severity estimation in several models, and reduced accuracy when tested on real field images. Overall, while the models show strong performance, there is a clear research gap in developing robust, real-time, and severity-aware systems suitable for practical agricultural deployment. As shown in the figure 7 MobileNet3 is the better choice for the researcher when the aim is to develop lightweight models for mobile or edge deployment.

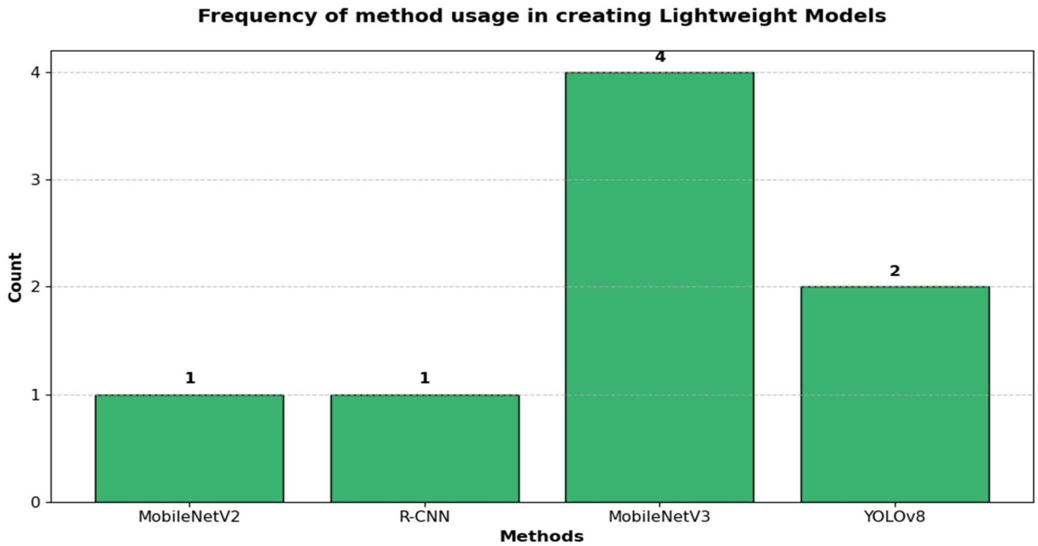

Figure 6: Methods used for developing lightweight models

5) What are the different Feature Extractions used in Convolutional Neural Network (CNN) for Leaf Disease Detection and Classification?

Table 4: Showing different feature extraction techniques used

SL NO	Reference	Feature Extraction Technique	Crop	Dataset used	Classification Accuracy achieved	Advantages	Drawbacks
1.	[8]	GLCM + Shape + Colour	Apple	PlantVillage Dataset	92.63%	Increases classification accuracy by combining multiple types of features	High dimensionality may lead to overfitting
2.	[9]	LBP+ HOG+ GLCM	Tomato,	Tomato Leaf,	92% 84.63%	Together, they provide a rich set of texture, shape, and color features for robust and accurate classification.	Increased dimensionality and computation.
3.	[10]	CNN	Pigeon Pea	Field Images	93.75%	Automatically extracts complex features, Highly effective in image-based tasks	Computationally expensive Risk of overfitting
4.	[11]	CNN (VGG16)	Pigeon Pea	Field Images	88%	Automatically extracts complex features, Highly effective in image-based tasks	Computationally expensive Risk of overfitting, especially with small datasets
5.	[12]	GLCM+ Color, Shape Descriptor	Pigeon Pea	Field Images	77.41%	capturing texture, color, and shape, improving classification.	Performance is sensitive to lighting, rotation, and background noise

The table 4 compares different feature extraction techniques and models used for crop disease classification, including GLCM-based methods, LBP, HOG, and CNN architectures like VGG16. The reported accuracy ranges from about 77% to 93.75%, with CNN-based approaches generally achieving higher performance due to automatic feature extraction. Combining multiple features such as color, texture, and shape improves classification accuracy but increases computational complexity. However, many methods suffer from issues like overfitting, high dimensionality, and dependence on large labeled datasets. Additionally, performance is often affected by real-world factors such as lighting, rotation, and background noise.

6) What is the inference taken by different Deep Learning models?

Inference Time: Time taken by a trained model to analyse an input (leaf image) and produce an output (predicted disease class). If the number of parameters is more, then inference time taken by the model will be more. Even inference time increases if the number of features extracted from diseased leaf increases. Inference time also depend on model layers and input image size. When these two increases inference time also increases.

This Table 5 compares the inference time of different deep learning models used for disease detection and classification on various crops. It provides insights how model architecture and number of parameters affect inference speed.

Table 5: Summary of DL models with inference times, dataset details, and model size

Sl. No	Reference	Crop	Inference Time	Number of images	Method	Model Size (No. of Parameters)	Dataset
1.	[13]	Maize	0.26sec	2112	RestNet-50	23.91million	Field images
2.	[14]	Wheat	6ms	10000	RestNet-50	100MB/15.8 million	Public Dataset
3.	[15]	Mulberry	4-12ms	6000	Modified MobileNet V3	100MB	Field Dataset
4.	[16]	Apple	2 seconds	54,000	Custom CNN	-	Plant Village

As shown in the Figure 7 YoLoV8 and MobileNetV3 are giving very fast inference so these two are ideal for real-time disease detection. ResNet-50 offers high accuracy, but very slow inference 0.26 seconds because number of parameters are very large around 23.91 million. CNN-based models like the one used for tomato show a good balance between speed and size.

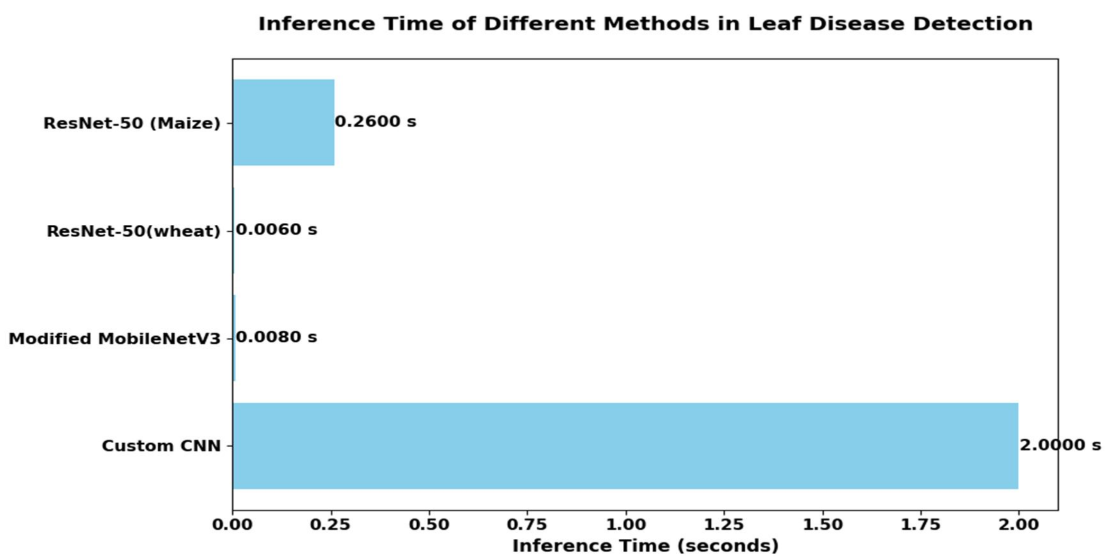

Figure 7: Inference time taken by different methods

7) What are the common Performance Metrics [ ] and Formulas used to measure the model?

DL models are measured using different performance metrics depending on the task. Common metrics include Accuracy, Precision, Recall, F1-score, Specificity, Inference Time, Loss and AUC-ROC.

8) Challenges

- The inadequacy of datasets constitutes one of the greatest challenge researcher's encounters when conducting their studies w.r.t few crops.
- Developing the lightweight DL model
- On-field Validation testing and continuous disease monitoring
- Severity detection of the diseases.
- Crop Disease detection by using the images of stem and root.

V. CONCLUSION

Deep learning methods, especially Convolutional Neural Networks (CNNs), have significantly contributed to plant disease detection and classification using leaf images. These models achieve high accuracy across different crops, supporting precision agriculture. However, their performance is often limited in real-world conditions due to environmental variations, noisy data, and the absence of disease severity assessment. Although considerable progress has been made, further improvements in model generalization, diverse datasets, and real-time deployment are essential to make these solutions more practical and accessible for farmers worldwide.

A. Future Scope

The future of plant disease detection focuses on developing robust, scalable, and interpretable models. Key areas include disease severity estimation, multi-crop and multi-disease classification, and deployment on mobile or edge devices for real-time field diagnosis. Floriculture crops like gerbera, rose, and jasmine remain underexplored. Additionally, most studies lack field validation and ignore diseases affecting stems and roots, which also impact crop yield.

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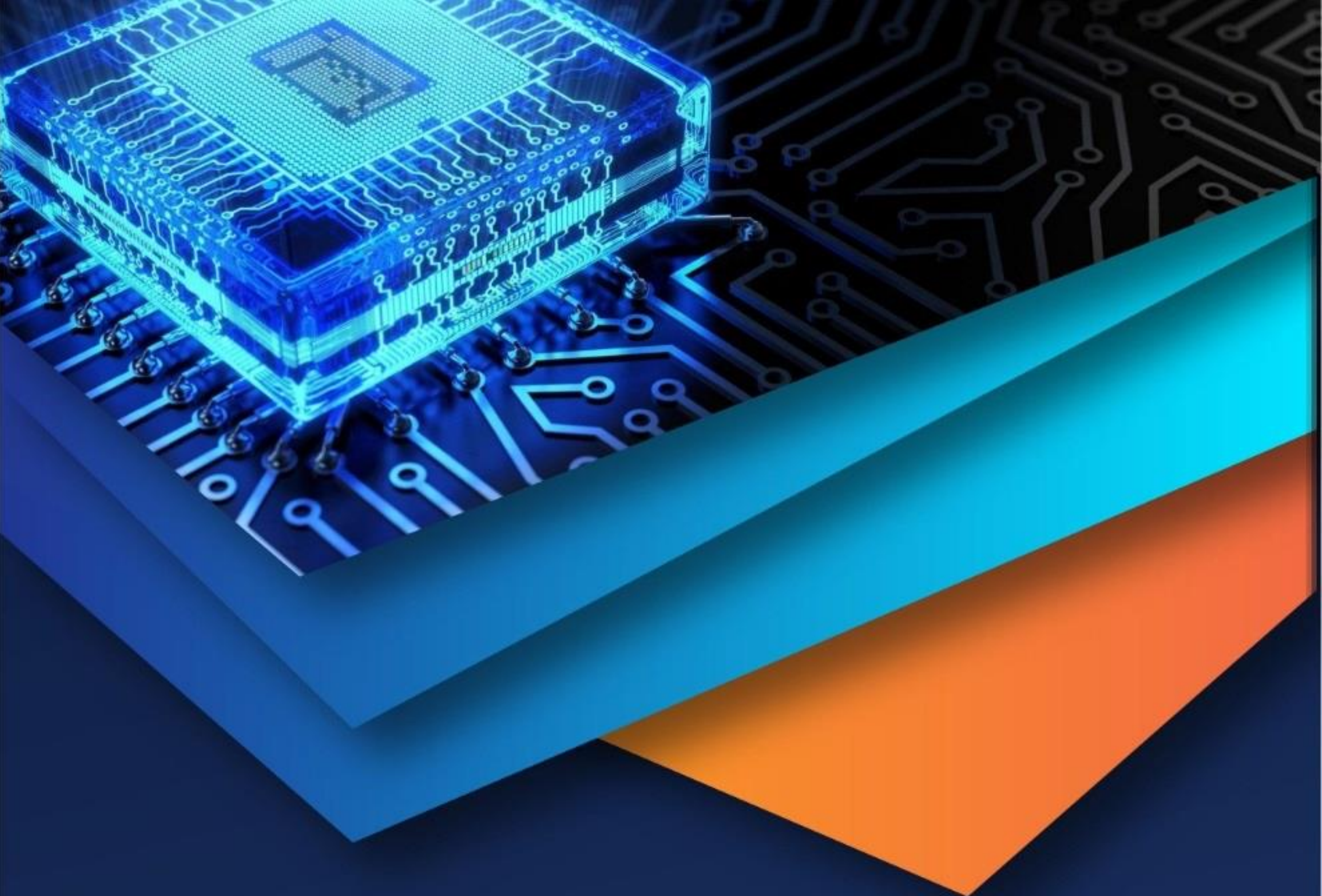

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