

**REVIEW ON SMART HARVEST: UNLEASHING AI AND ML  
TECHNIQUES FOR DISEASE IDENTIFICATION IN AGRICULTURAL  
PLANTATIONS**

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**Abstract**

One of the ongoing issues for farmers is plant disease, which puts their livelihood and access to food at risk. Finding diseases in plants or crops is problematic since analyzing each crop in significant areas requires too much time, effort, labor, and knowledge. The concept of agriculture is wholly altered by intelligent farming, which also helps to improve the quality and output of food products. It also aids in efficiently using the labor force needed for production. It is imperative in such a situation to guarantee that the crops are healthy and free from diseases. This paper uses convolutional neural network architectures to review contemporary deep learning-based strategies for various plants. This article will examine several machine-learning and deep neural network technologies. These techniques are used to recognize plant diseases from the images of infected plants. We conducted a thorough analysis of the volume of papers covering various plant diseases and other plants and fruits, and we evaluated these papers following crucial criteria. These factors include the number of classes (diseases), pretreatment, segmentation approach, classification type, classification accuracy, and size of the picture data set. This study aims to review several Internet of Things (IoT), deep learning, machine learning, and artificial intelligence (AI) methods and models to provide disease detection solutions and find the most appropriate model to achieve higher accuracy and precision.

**KEYWORDS:** Plant diseases, learning techniques, Artificial Intelligence, Internet of things, Prediction techniques.

**ABBREVIATIONS**

|      |                                     |
|------|-------------------------------------|
| ARM  | Artificial Removal Module           |
| CAE  | Convolutional Autoencoders          |
| CFS  | Correlation-Based Feature Selection |
| HSI  | Hyper Spectral Imaging              |
| LBP  | Local Binary Pattern                |
| SCFT | Scale Invariant Feature Transform   |
| KMC  | K-means Clustering                  |
| SGD  | Stochastic Gradient Descent         |
| SNR  | Signal-To-Noise Ratios              |
| EL   | Ensemble Learning                   |
| DL   | Deep Learning                       |
| DT   | Decision Trees                      |
| TL   | Transfer Learning                   |
| BM   | Bayesian Models                     |
| SVMS | Support Vector Machines             |
| CV   | Computer Vision                     |
| AUC  | Area Under Curve                    |
| FN   | False Negative                      |
| FPR  | False Positive Rate                 |
| FP   | False Positive                      |
| GAP  | Global Average Pooling              |
| GLCM | Grey Level Co-Occurrence Matrix     |
| MAE  | Mean Absolute Error                 |
| MSE  | Mean Squared Error                  |
| ROC  | Receiver Operating Characteristic   |
| TN   | True Negative                       |
| KNN  | K-Nearest Neighbours                |
| RF   | Random Forest                       |
| DCNN | Deep Convolution Neural Network     |

|         |  |
|---------|--|
| ENNS    | Ensemble neural networks                           |
| LASSR   | Leaf Artifact-Suppression Super-Resolution         |
| LVQ     | Learning Vector Quantization                       |
| LSTM    | Long Short-Term Memory                             |
| LSCNN   | Self-Structured Convolution Neural Network         |
| VGG     | Visual Geometry Group                              |
| SCNN    | Sequential or Shallow Convolutional Neural Network |
| FAA     | Food And Agriculture                               |
| GUI     | Graphical User Interface                           |
| HH      | Halyomorpha Halys                                  |
| BMSB    | Brown Marmorated Stink Bug                         |
| MCU     | Microcontroller Unit                               |
| NLB     | Northern Leaf Blight                               |
| CC      | Cloud Computing                                    |
| PEDS-AI | Pest Early Detection System                        |
| PPP     | Plant Protection Products                          |
| RM      | Research Methodology                               |
| UAV     | Unmanned Aerial Vehicle                            |
| PVD     | Plant Village Dataset                              |
| DS      | Dataset  |

## **I. INTRODUCTION**

India possesses the world's second-largest agricultural land area, with over half its population engaged in agriculture, making farmers a crucial component in the food supply chain. With approximately 55% of its population dependent on agriculture for their livelihoods [1].

Pesticides may be divided into several categories: herbicides, insecticides, bactericides, fungicides, etc. Insecticides and herbicides, for example, have been widely employed by farmers to manage plant diseases and pests and boost agricultural yields. Pests frequently have proliferated and to get rid of the pests and to reduce damage, a substantial amount of pesticides should be used on the crops. However, pesticide residues persist even after washing crops treated with pesticides throughout the growing season. These substances boost plant yields in the short term without affecting crop quality. However, Herbicides, for example, damage the environment and the ground where they are employed in the long run,

which is bad for health. In addition to harming the environment and agriculture, the indiscriminate and excessive use of poisonous synthetic pesticides has infiltrated the food chain, impacting all living things. In addition to its ability to eradicate and manage pests through its toxicological properties, it also poses an unintentional threat to humans, the environment, and other harmless and beneficial soil bacteria and others that are exposed accidentally to these products. Because human enzymes or microbes cannot break down certain pesticides, they build up in tissues, soil, and plants and cause various issues [2].

Regardless of the strategy and approach, the first step in effective disease management is accurate identification and timely remedial action. A sophisticated and precise analysis is necessary when certain illnesses have no obvious symptoms, or the risks become apparent too late to be effective. The traditional approach to identifying any disease pest relies mainly on visual inspection manual checks.

As an alternative, current advancements in artificial intelligence (AI)-based technologies have been demonstrated how to automate plant disease detection (PDD) accurately and quickly. This marks the onset of the modern era of agriculture [3]. The major challenge of describing disease symptoms for computer-based identification has been addressed by deep learning. In this approach, models learn the characteristics through optimization rather than relying on explicitly defined symptom attributes. During training, the neural network learns to extract features, which can subsequently be utilized for disease spot detection, classification, and prediction.

This study aims to comprehensively evaluate modern agricultural studies and research using artificial intelligence to address various relevant problems.

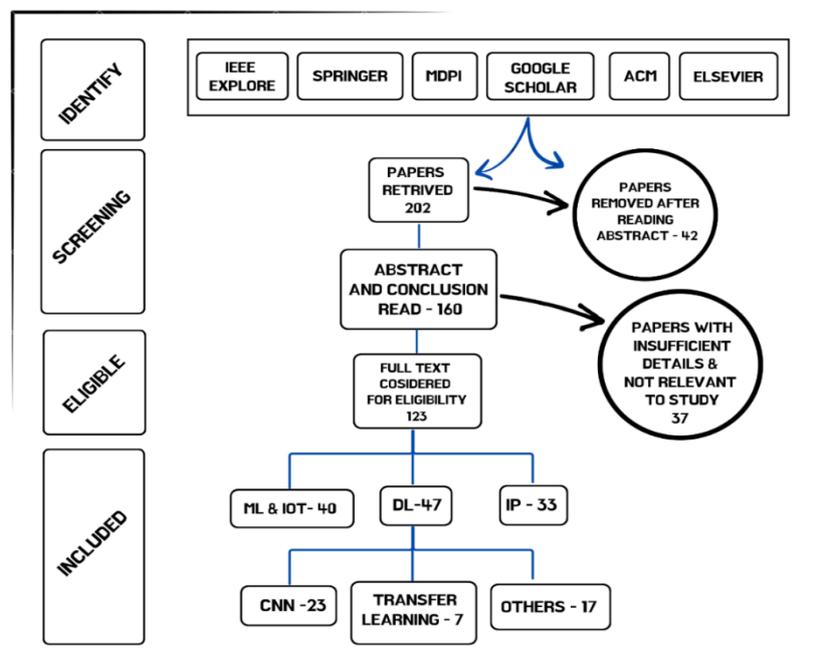


Figure 1: Searching and filtering approach of resources for the study

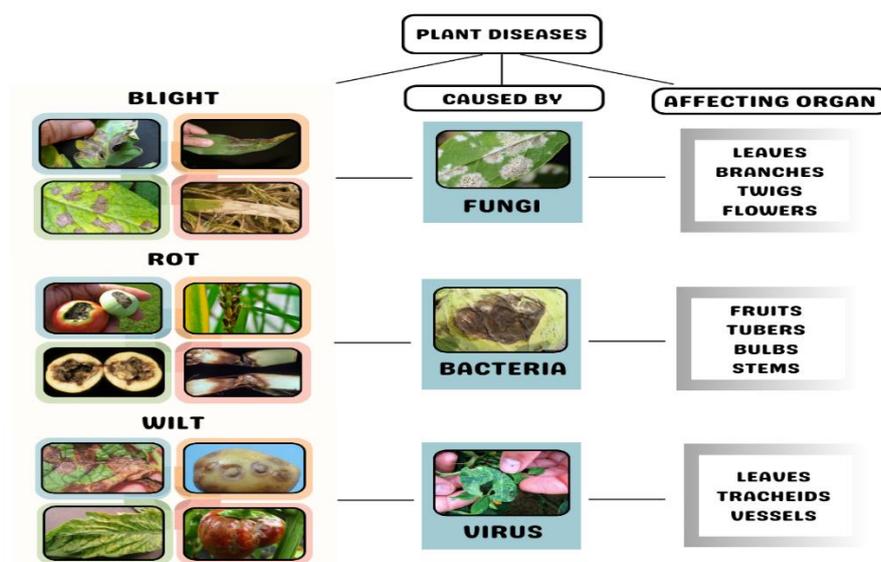
Additionally, it thoroughly assesses the drawbacks, advantages, and key characteristics of various techniques in practical contexts. For this review, different publications were found after searching five central academic research databases: IEEE Xplore, Springer, Elsevier, Google Scholar, Social Science Research Network (SSRN), IJAEML, Applied Sciences (MDPI), and Frontiers [4]. Based on the significance of the proposed methodologies and their performance, a total of 125 studies were selected after filtering some more publications by going over their abstract and conclusion that did not align with our study area. Figure 1 shows the foraging and filtering approach followed in gathering the resources for the study.

Section II provides a background study, which details the background work done for this paper and a detailed overview of the many forms of leaf stress(es) encountered on diverse plants. Section III investigates the literature survey for the PDD. Section IV illustrates the fundamentals of the survey process, including the review questions and strategies. Section V reviews recent research on PDDs and a detailed discussion of the results. Finally, Section VI presents the review's findings and suggestions for future trends

**II. BACKGROUND STUDY**

Plant diseases are a significant source of distress for agriculturalists worldwide. Pathogens are microbes that cause the vast majority of plant stressors. Stress may be classified as biotic or abiotic, depending on the pathogen.

Insufficient soil moisture and nutrient shortages/excesses, among others [5]. Fortunately, abiotic stressors are readily avoided by removing causes such as insufficient soil moisture and nutrient shortages/excesses. Living organisms produce biotic or infectious plant diseases, as previously stated. While fungi cause most biotic plant illnesses (about 70%), additional plant pathogens exist. Figure 2 shows the classification of plant diseases.



**Figure 2:** Classification of plant diseases

1. **Fungal Stresses:** Fungal infections may damage numerous plant sections, such as leaves, stems, roots, and fruits, causing wilting, yellowing, lesions, and malformations. Powdery mildew, downy mildew, rusts, and smuts are well-known for lowering crop yields and resulting in economic losses. These fungi interfere with plant growth and development, nutrient and water intake, and can even cause plant death in severe circumstances.
2. **Bacterial Stresses:** Bacterial biotic diseases in plants pose a substantial hazard to crops and natural ecosystems. Bacterial pathogens, including *Xanthomonas*, *Pseudomonas*, and *Erwinia* species, can infect plant tissues, causing symptoms such as leaf spots, wilting, cankers, and stunted growth. These diseases can destroy agricultural production, reduce the quality of produced produce, and cause farmers to lose money. Bacterial wilt, citrus canker, and fire blight are plant diseases produced by bacteria that have significantly influenced agriculture.
3. **Viral Stresses:** Viral infections infect a wide range of plant species, generally by vectors such as insects or mechanical methods, causing a slew of symptoms such as mosaic patterns, yellowing, stunting, and malformations. Viruses interfere with plants' natural physiological processes, decreasing yields, diminishing the quality of harvested goods, and frequently leaving infected plants unmarketable. Preventive strategies, including using virus-free planting materials, reducing insect vectors, and following stringent sanitation standards, are crucial in managing viral plant diseases.

A Real-time PDD continues to be complicated for a few reasons despite the contributions of the fantastic projects that are now accessible. The aim of this review is to:

1. Outline methodologies, datasets that are accessible, and difficulties in detecting plant diseases that must be overcome to create novel agricultural tools for observing and early detection of plant diseases.
2. Demonstrate a thorough data gathering and pre-processing technique for PDD, and the paper also reviews and provides information on all publicly available datasets that can be used for research.
3. Examine three essential techniques namely deep learning, machine learning, and image processing on plant diseases and their potential use in Internet of Things (IoT) based intelligent agricultural solutions.

The expanding global population underscores the importance of agriculture, an industry often overlooked but crucial for sustainability. In 1983, agriculture saw its first computer usage reports [6], beginning a technological transformation. McKinion and Lemmon pioneered AI methods for crop management in their 1985 essay, "Expert Systems for Agriculture" [7]. In 1987, Riach et al. introduced the expert system POMME for managing apple plantings [8], representing a notable development in agricultural technology. Given the extensive evaluation of machine learning (ML) and deep learning (DL) techniques in agriculture, there is a pressing need to conduct a comprehensive analysis of image-based plant disease detection. This field is gaining importance as it plays a pivotal role in ensuring the sustainability of agriculture in the face of a growing population.

Figure 3 shows the percentage depiction of AI domains that are recently, an assessment of the effectiveness of current PDD techniques, including those for segmentation, classification, localization, and disease, was carried out. Studies [9] and [10] mainly concentrated on the CNN model as it is employed in the PDD and showed that there is still a gap to be filled in enhancing the approaches when considering identical visual environments, respectively. Zahid Iqbal et al. [11] examined the research on utilizing classical IP to detect citrus plant diseases. They compared the performance of several strategies based on data pre-processing, feature extraction, classification, and segmentation. They noticed that the segmentation method known as k-means was frequently used to localize plant diseases. Ali et al. [12] concentrated on IP-based approaches, fluorescence spectroscopy, hyperspectral remote sensing, visible and infrared (IR) spectroscopy, and electric impedance spectroscopy to identify plant diseases. The effectiveness of classical ML and DL-based plant disease detection approaches was assessed for five essential cash crops—rice, wheat, maize, soybeans, and barley Manavalan [13]. The pros and cons of various picture pre-processing, segmentation, feature extraction, feature selection, and classification techniques were also noted. Much study has been done on image-based plant disease detection, and several researchers have examined the field's advancement with various goals.

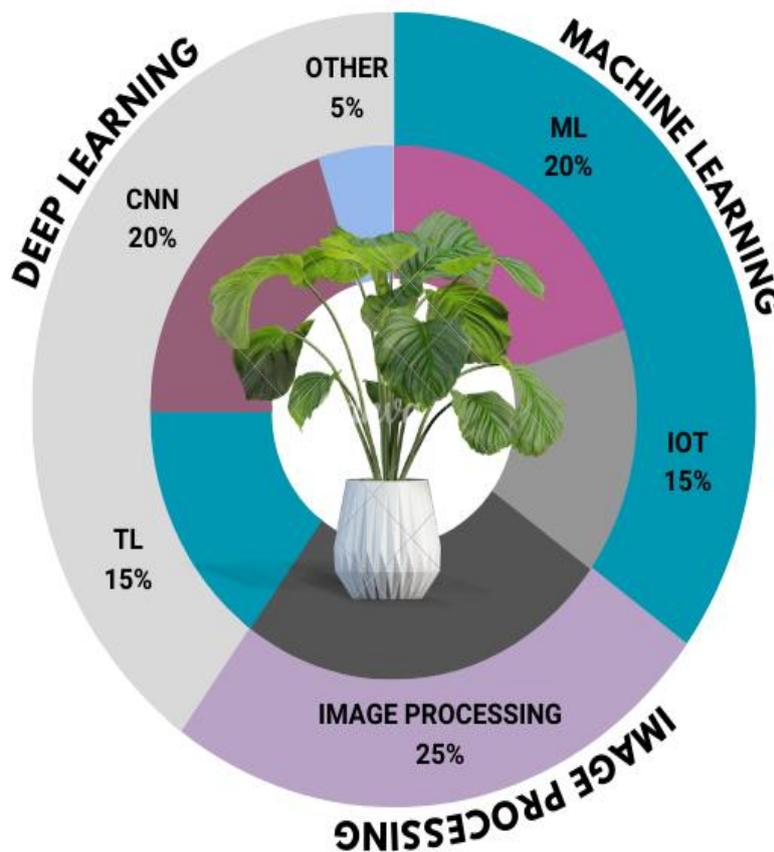


Figure 3: Percentage depiction of AI domains

#### **IV. REVIEW QUESTIONS**

In addition to this significant research topic, several secondary questions are raised to help select effective plant disease detection techniques. In this step, the selection criteria will be reviewed and summarized to evaluate the effectiveness of current CNN models in detecting diseases in diverse crops using training and test data sets. For the following research problems, the entire review procedure is carried out by looking at the current CNN model solutions. Seven research questions are addressed using data from chosen studies and Research Methodology (RM) findings. These days, deep learning is receiving much attention and is developing into an active study area. Although the DL architecture takes a while to train the neurons, it achieves impressive classification accuracy and a high rate of object identification.

RQ1: Are enough publicly accessible datasets to create effective deep learning and machine learning models to detect plant diseases?

RQ2: What are the analytical methods and essential pre-processing procedures, along with the imaging sensors, employed to enhance image quality and the process of image capture?

RQ3: What are the metrics for analysing the efficiency of artificial intelligence systems most effectively identifying and classifying plant diseases?

RQ4 How do CNN and transfer learning to facilitate plant disease detection?

RQ5: Which image processing (IP) and feature extraction methods are chosen from deep learning algorithms?

RQ6: How does IOT-assisted technology help in PDD and management, and what is auto-encoder hype?

RQ7: How can optimization of the loss function between training and test datasets be achieved while mitigating the overfitting problem?

#### **V. RESULTS AND DISCUSSIONS**

***RQ1: Are enough publicly accessible datasets to create effective deep learning and machine learning models to detect plant diseases?***

Deep learning implies the need for data to train the model. To attain excellent precision, tens of thousands of photos are often required. Obtaining a massive amount of real-world field data is a significant challenge in plant stress identification, among other issues. Researchers have made significant contributions in the area by creating databases for various crops and making them available to the scientific community. Consequently, several databases comprising a variety of plant diseases are openly accessible. Pictures generated some datasets in a lab with the backgrounds adjusted or eliminated, while others were made by taking pictures in agricultural fields. The most popular publicly accessible datasets used by researchers to develop methods for illness detection are described in this section, the Figure 5

shows the publicly available datasets in a graphical representation. The datasets are also listed in Table 1, and some sample pictures from these datasets are shown in Figure 4.

1. *Plant Village Dataset* – The Plant Village Dataset is extensively utilized for developing Plant Disease Detection (PDD) models and is a popular choice among researchers. Penn State University created it in collaboration with a Swiss counterpart and includes 61,486 images of plant leaves, categorized into 38 groups based on species and diseases. Six augmentation techniques, such as scaling, rotation, noise injection, gamma correction, picture flipping, and PCA colour augmentation, were applied to enhance diversity. However, the dataset poses challenges due to lighting and background setting variations during image capture [14].

2. *NLB dataset* - The NLB dataset comprises 18,222 field photos of maize infected with Northern Leaf Blight (NLB), which was obtained using various methods, including UAS-based airborne photography and handheld imagery. This dataset includes 105,735 lesion annotations on real-field images. It specifically focuses on diseased maize leaves, making it suitable for training deep-learning models to distinguish between healthy and infected plants or locating NLB lesions [15].

3. *Cassava disease dataset* - The Cassava Disease Dataset is a recent collection of field images featuring cassava diseases. It includes 5,656 photos categorized into five distinct disease classifications: healthy, cassava bacterial blight, cassava brown streak disease, cassava green mite, and cassava mosaic disease. The dataset offers diverse backgrounds and field conditions, making it useful for training algorithms to recognize cassava infections in practical settings [16].

4. *PlantDoc*: PlantDoc is a dataset containing 2,569 images covering 30 classes, including diseased and healthy plants and 13 different plant species. These images, collected from the internet, have been annotated to train algorithms in identifying crop diseases from field conditions. The image quality varies; some photos resemble laboratory images rather than those captured in the field [17].

5. *LWDCD2020 dataset* - The Large Wheat Disease Classification Dataset 2020 (LWDCD2020) comprises 12,160 images of wheat diseases, divided into nine disease classes and one healthy class, collected under actual field conditions [18].

6. *Digipathos Dataset* - The Digipathos Dataset is a substantial collection featuring 46,513 photos, encompassing 171 illnesses affecting 21 crops. However, most of these images do not depict plant diseases in realistic field settings, as they predominantly consist of clipped disease lesions [19].

7. *DiaMOS plant dataset* - The DiaMOS Plant Dataset covers the entire growing season of a pear tree, offering 3,505 photos for classification and detection tasks. It includes 499 fruit images and 3,006 foliage images captured in four stages, from fruit set to nut fruit [20].

8. *RoCoLe Dataset* - The RoCoLe Dataset includes images of robusta coffee leaves, totaling 1,560 pictures of both the upper and lower surfaces of coffee leaves, showcasing healthy and diseased states as well as the presence and extent of illness [21].

9. *Apple dataset* - The Apple Dataset includes 3,651 images of apple leaves with various diseases, which were used in an illness identification competition on the Kaggle platform. The images are categorized into four groups: healthy leaves,

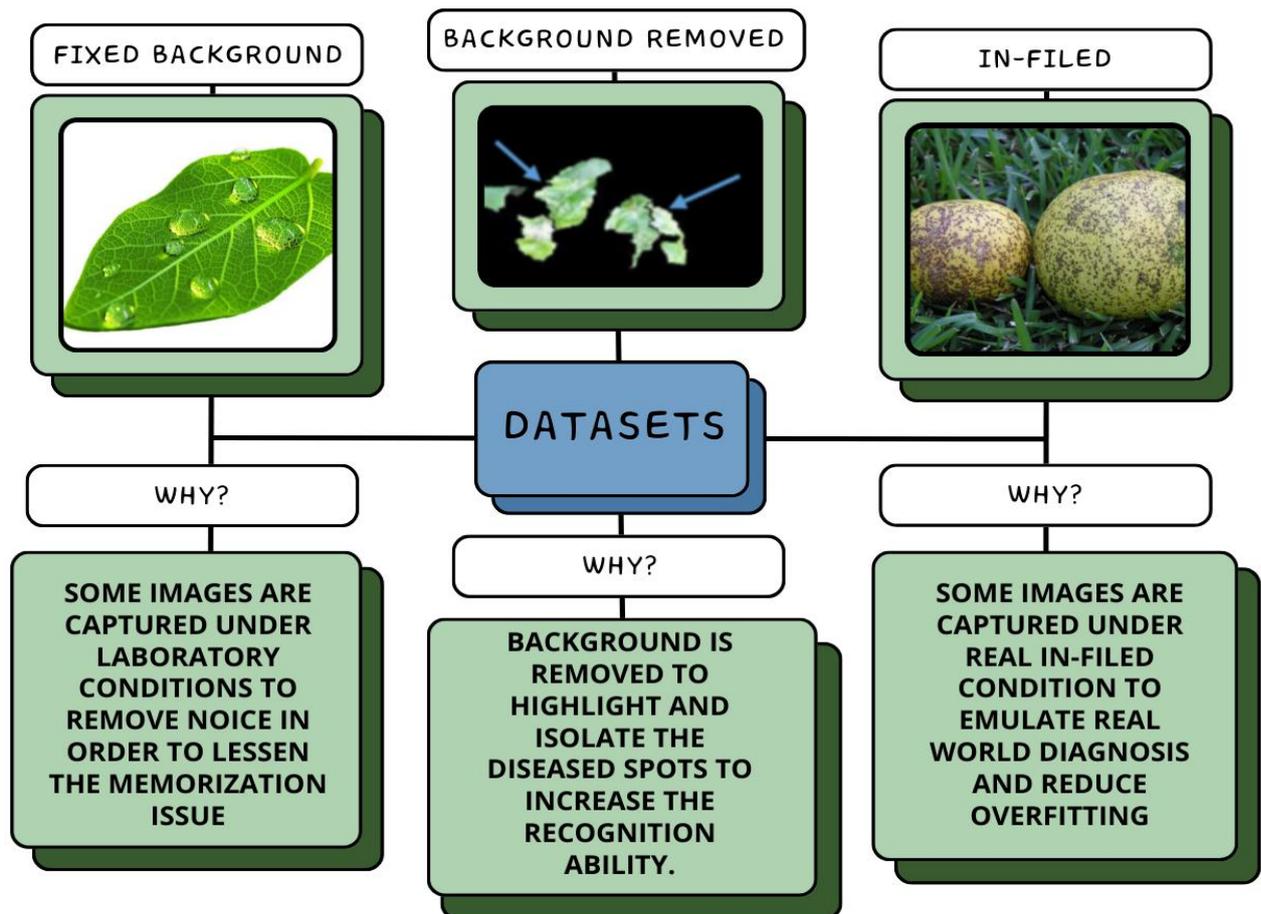


Figure 4: Some Images from the existing Datasets

apple scab, cedar apple rot, and other diseases [22].

10. *BRACOL dataset* - The Brazilian arabica coffee leaf dataset, known as BRACOL, contains 1,747 images of arabica coffee leaves affected by various biotic stressors, such as leaf miner, leaf rust, brown leaf spot, and cercospora leaf spot. The photos were taken in Brazil's mountainous areas under different lighting and capture conditions [23].

11. *AES-CD9214 dataset* - The AES-CD9214 Dataset comprises 9,214 photos taken under field conditions, featuring a variety of lighting, angles, resolutions, and capture settings. It includes 44 different plant leaf types in six classes [24].

12. *Plant Pathology dataset* - The Plant Pathology Dataset includes 3,651 RGB images of apple foliar disease signs taken in a non-sprayed apple orchard. These images depict various apple diseases, including apple scab, cedar apple rust, complicated disease signs, and healthy leaves, captured in different lighting, angles, surfaces, and noise conditions [25].

13. *Embrapa Dataset*: The Embrapa Dataset, initially the PDD Database, has been expanded into the XDB dataset, containing 46,513 images of maize leaves from 18 species and 93 disease categories, covering various plant components infected by diseases [26].

Table 1: Abstract of the datasets available

| <b>Datasets (DS)</b> | <b>No. of Classes</b> | <b>No of images</b> | <b>Background choice</b>     | <b>Reference</b> |
|----------------------|-----------------------|---------------------|------------------------------|------------------|
| LWDC2020             | 10                    | 12160               | Laboratory and in-field both | [18]             |
| PlantDoc             | 30                    | 2569                | Infield                      | [17]             |
| Cassava              | 5                     | 5656                | In-field                     | [16]             |
| NLB                  | 1                     | 18222               | In-field                     | [15]             |
| PlantVillage         | 38                    | 61486               | Both                         | [14]             |
| Apple DS             | 5                     | 3651                | In-field                     | [22]             |
| RoCoLe DS            | 6                     | 1560                | In-field                     | [21]             |
| DiaMOS DS            | 8                     | 3505                | In-field                     | [20]             |
| Digipathos DS        | 400+                  | 46,513              | Both                         | [19]             |
| Plant Pathology DS   | 3                     | 3651                | Both                         | [25]             |
| AES-CD9214 DS        | 6                     | 9214                | In-field                     | [24]             |
| BRACOL DS            | 5                     | 1747                | Both                         | [23]             |
| Embrapa DS           | 93                    | 46,513              | Both                         | [26]             |

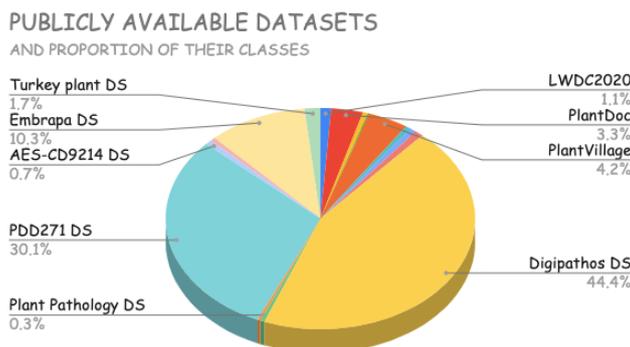


Figure 5: Publicly available datasets

2. RQ2: What are the analytical methods and essential pre-processing procedures, along with the imaging sensors, employed to enhance image quality and the process of image capture?

Pre-processing allows us to eliminate unwanted distortions while enhancing specific features and characteristics essential for the application we are working on. Researchers have utilized various cell phones, digital SLR cameras, and scanning equipment to collect data. Data gathering also involved the usage of UAVs. Spectrometers, lamps, and CMOS cameras were used to gather data for hyperspectral imaging. Many pre-processing approaches are used in classical IP and ML methodologies to detect plant diseases. However, most DL approaches employ image scaling, image normalization, and data augmentation techniques for picture preparation tasks [27].

An enormous amount of visual data is used to train deep learning models to make the data consistent. The model may find it challenging to train if the photos in the dataset have different sizes, formats, and other characteristics. The photographs can be normalized using pre-processing methods, such as scaling them to the same size and converting them to the same format. Noise and distortions, such as sensor noise, compression artifacts, and dust spots, may frequently be found in images. Denoising and filtering are two pre-processing methods that may eliminate this noise and boost the image's quality. Different methods can be used to acquire images, which might cause data to be inconsistent. For instance, some pictures may be darker or brighter than others or be shot from multiple angles. The backdrop of a picture may occasionally include unimportant details that disturb the model or add noise. Remove the backdrop to isolate the main features of interest using techniques like pictures [28].

Table 2: Summary of the pre-processing strategies

| REFERENCE | MODE OF ACCESS | PRE-PROCESSING  | PLACE              |
|-----------|----------------|---|--------------------|
| [11]      | Camera         | Edge detection & threshold-based segmentation, color space structure resizing, shadow | Agricultural Field |

|      |  |   |  |
|------|--|---|--|
|      |  | removals, K-mean (GLCM).  |  |
| [21] | 5-MP smartphone camera                       | Multiple backgrounds, brightness, and temperature levels.   | CIIDEA, Calceta, Manabí, Ecuador                         |
| [29] | Canon EOS 80. DSLR camera, UAV, DJI phantom. | HSV, Background removal, and segmentation using SVM.  | Tianjingshan National Forest Park.                       |
| [30] | –  | Normalization and augmentation, resizing, mirroring.  | Dataset  |
| [36] | Canon EOS 1300 DSLR                          | Rescale, Rotation, Resize   | Pakistan   |
| [40] | BM-500GE/BB-500GE digital color camera       | geometrical intensity transformation, hue saturation.   | Cucumber planting bases of Yangling agri industry, China |
| [41] | UAV, Camera                                  | Normalization, flip, edge sharpening, Gaussian noise addition, and Gaussian blur gamma contrast adjustment. | Longan orchard, China                                    |
| [42] | Nikon Coolpix S3100.                         | Thresholding, clustering (k-means, mean-shift, fuzzy-c-means). Contrast stretching.                         | Dataset Kaggle   |
|      | HR camera devices                            | Novel artifact removal module (ARM) using LASSR   | Japan, taken during the period 2015–2019                 |
| [43] | Digital-SLR Camera                           | Resizing, random flipping, k-means  | Chennai, Tamil Nadu, India                               |
| [44] | Database(PlantVillage)                       | Gamma correction, noise injection, PCA color AUG, rotation, scaling.  | –  |
| [51] | 18MP Smartphone camera                       | Converting RGB into L*a*b   | Muara Wahau, East Borneo, Indonesia                      |
| [53] | MCU-based OV5640 5MP resolution              | Gaussian blur/smoothing filter and histogram-based  | Laboratory conditions                                    |

|      |                            |   |  |
|------|----------------------------|---|--|
|      | imaging sensor.            | thresholding.   |  |
| [56] | 48MP CMOS camera using UAV | Spectral-gating Denoising, Noisere-duce python library's denoise function, MixIT                      | Terrain and vegetations                      |
| [60] | Smartphone camera          | Multitudinous law for resizing and clustering   | –  |
| [63] | Mobile camera              | HSI, controlled illumination of two 400 W halogen lamps.  | Tea Plantation                               |
| [64] | Smartphone camera          | Resize, Grayscale   | Wheatfield, India                            |
| [65] | Mobile camera              | Gaussian noise processing, resizing, flipping   | Apple Experiment St Northwest A&F Uni, China |
| [66] | Mobile Camera              | Histogram equalization, green masking, mean shift clustering.   | Laboratory                                   |
| [67] | Canon EOS DSLR Camera      | Histogram equalization, DTCWT, DWT, ranklet transformation  | Banana Research Station, Kerala.             |
| [68] | –                          | HSV Model, 3Dbox Filter, and Gaussian Filter method   | Laboratory conditions                        |
| [69] | Mobile Camera              | K-MEANS, Binarization, Resize, Clusters in the GUI (L*a*b space)                                      | –  |
| [70] | Internet                   | Transformations like Rotations, Shifting, Zooming Brightness, and Flipping.                           | –  |
| [71] | Database(PlantVillage)     | Constancy algorithm, DEXTR HSI and LAB-based hybrid segmentation, Gaussian noise reduction, resizing. | –  |

|      |                        |  |   |
|------|------------------------|--|---|
| [72] | Database(PlantVillage) | Background removal based on hue values, reducing image dimensionality, 3Dbox and Gaussian Filter, RGB into HSV, K-means. | — |
|------|------------------------|--|---|

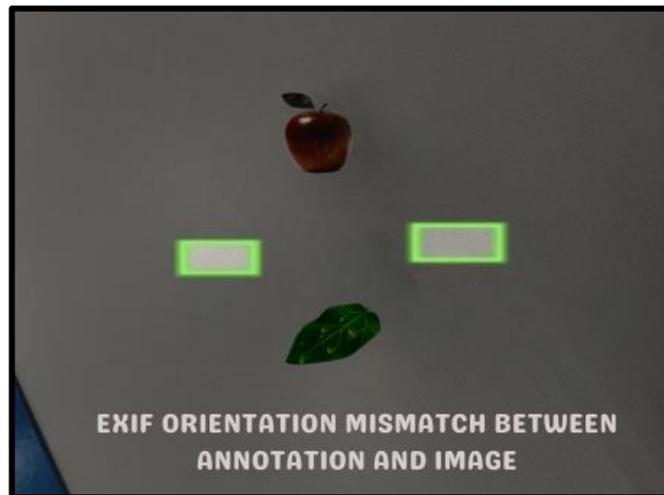


Figure 6: Depicting orientation mismatch



Figure 7: Depicting the correct match.

segmentation or background removal. To provide the model with more training samples, picture augmentation involves adjusting photos to produce several versions of the same

material. For instance, randomly changing an input picture's orientation, brightness, or size necessitates that a model considers how the image subject may seem under various lighting conditions. Augmenting existing training data allows the model to learn from a more extensive range of events by enhancing the training data to generalize to different scenarios. This is especially crucial when the acquired datasets could be small. Because a deep learning model will (over)fit the training instances, introducing diversity into the input pictures allows for creating fresh, practical training examples. Table 2 depicts the various pre-processing techniques researchers have taken into account.

The information (metadata) recorded with a picture when captured instructs our machines how to display the input image and how it is stored on disk. We have trained the model incorrectly if a model is "seeing" a picture differently from how it is "perceived" to be orientated despite annotation's inbound boxes. This metadata is called its EXIF orientation. This instruction, contained in the EXIF orientation field, accelerates the encoding of the picture at the moment of capture, allowing cameras to sample data from their sensors effectively and without unintended artifacts. Sadly, this may result in problems if the program showing the photographs is ignorant of the metadata and carelessly shows the image without considering its EXIF orientation. This is an easy thing to mess up. It is one of the flaws found most frequently in computer vision projects [29]. You may give your model incorrect information without realizing it if some of your photos are saved on disk as x,y and others as y,x. Moreover, this issue can be fixed by auto-orientation. Figure 6 shows the EXIF Orientation mismatch between annotation and image, and the Figure 7 shows the Correct Exif Orientation.

*3. RQ3: What are the metrics for analyzing the efficiency of artificial intelligence systems most effectively identifying and classifying plant diseases?*

Numerous assessment criteria have been developed for evaluating the effectiveness, performance, and efficiency of vision-based methods and the diverse machine-learning approaches under examination. The selection of commonly employed evaluation measures hinges on whether the model is geared towards binary-class or multi-class classification. These metrics encompass Accuracy, Logarithmic Loss, the Confusion matrix (encompassing TP, TN, FP, FN), Area Under Curve (AUC), F1 Score (comprising Precision and Recall), Mean Average Precision (mAP), Mean Squared Error (MSE), and Mean Absolute Error (MAE).

Accuracy, often called predictive accuracy, is a metric used in machine learning and statistics to assess the performance of a model. It quantifies the proportion of correct predictions made by the model among the total number of collected samples (T) as per the below equation,

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions made}}$$

(1)

For example, let us consider a situation in our training dataset where 98% of the samples belong to class A, and only 2% belong to class B. In this scenario, our model can quickly

achieve a high % training accuracy of 98% by predicting that every training sample falls into class A. However, when we test the same model on a different dataset where 60% of the samples are from class A and 40% are from class B, the test accuracy drops to 60%. This discrepancy illustrates that while Classification Accuracy appears impressive, it can be misleading and give a false impression of high accuracy [30].

The Confusion Matrix provides a valuable breakdown of the model's performance, involving four key terms:

**True Positive (TP):** These are instances where our model predicted "YES," and the actual result is indeed "YES."

**True Negative (TN):** These instances occur when our model predicted "NO," and the actual result is also "NO."

**False Positive (FP):** These are instances when our model predicted "YES," but the actual result is "NO."

**False Negative (FN):** These are instances when our model predicted "NO," but the actual result is "YES."

These terms are particularly relevant when the model is engaged in binary classification tasks.

$$\text{Accuracy} = \frac{TP+TN}{T}$$

(2)

The F1-Score - can be described as the Harmonic Mean of both recall and precision. Its values fall between 0 and 1, offering insights into two crucial aspects of your classifier or model. Firstly, it gauges the model's accuracy in correctly classifying examples, highlighting what percentage of instances it gets right. Secondly, it assesses the model's ability to avoid missing instances, indicating what percentage of relevant examples it correctly identifies as shown below,

$$F1 = 2 * \frac{1}{\frac{1}{precision} + \frac{1}{recall}}$$

(3)

Precision - is determined by dividing the number of true positive results (correctly predicted positive instances) by the total number of positive results the model has classified. It can be determined as shown below,

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

(4)

Recall - is computed by taking the number of positive samples correctly classified as positive and dividing it by the total number of all positive samples, which includes all the samples that should have been labelled as positive by the model. This metric assesses the model's ability to identify all relevant positive instances as shown below,

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

(5)

Logarithmic Loss - often called Log Loss, is an effective metric for evaluating classification models, especially in scenarios involving multiple classes. Its operation involves penalizing incorrect classifications. To compute Log Loss, the classifier is required to assign probabilities to each class for every sample. If we have a dataset with N samples distributed among M classes, Log Loss is calculated as follows:

$$\text{Logarithmic Loss} = \frac{-1}{N} \sum_{i=1}^N \sum_{j=1}^M Y_{ij} * \log (P_{ij})$$

(6)

Log loss ranges from  $[0, \infty)$ , and A log loss closer to 0 suggests better precision. In contrast, a log loss farther from 0 indicates lesser accuracy, where  $Y_{ij}$  specifies whether or not sample  $i$  is a member of class  $j$  and  $P_{ij}$  represents the likelihood that sample  $i$  belongs to class  $j$ .

The ROC (Receiver Operating Characteristic) curve is a visual representation that shows how effectively a classification model performs across various classification levels. It is a graphical plot that compares the True Positive Rate (TPR), also known as Sensitivity, to the False Positive Rate (FPR) as shown below.

$$TPR = \frac{TP}{TP+FN}$$

(7)

$$FPR = \frac{FP}{FP+FN}$$

The AUC, which stands for area Under the ROC Curve, quantifies the complete two-dimensional area beneath the ROC curve. Its values range from 0 to 1, and our model's performance improves as this value increases [31].

#### *4. RQ4: How do CNN and transfer learning to facilitate plant disease detection?*

CNNs, especially Convolutional Neural Networks, excel in handling image data and gathering crucial spatial and temporal information for tasks like image classification and computer vision applications. Two deep learning approaches, Convolutional Autoencoders (CAEs) and Convolutional Neural Networks (CNNs), are widely embraced in computer vision applications due to their excellent performance with image data. Figure 8 shows the architecture of training CNN from scratch and using the same CNN to train another model using Transfer Learning.

Rakesh et al. [33] introduced Inception V3 and ResNet-9 models on the Plant Village and New Plant Disease Datasets. They utilized Explainable AI (XAI) tools like LIME and Grad-CAM to explain their model's predictions visually. The results showed high accuracy, with ResNet achieving a validation accuracy of 99.2% and Inception V3 reaching 95.46%.

Hemavathi et al.[34] employed the CNN AlexNet architecture with hyperparameters tuned for plant leaf datasets collected from GitHub and Kaggle. Their proposed model achieved an accuracy of around 97.5%.

Peng Jiang [35] introduced a novel deep CNN model called VGG-INCEP for apple leaf disease detection, outperforming various conventional networks with an overall detection performance of 78.80% mAP and a detection speed of 23.13 FPS.

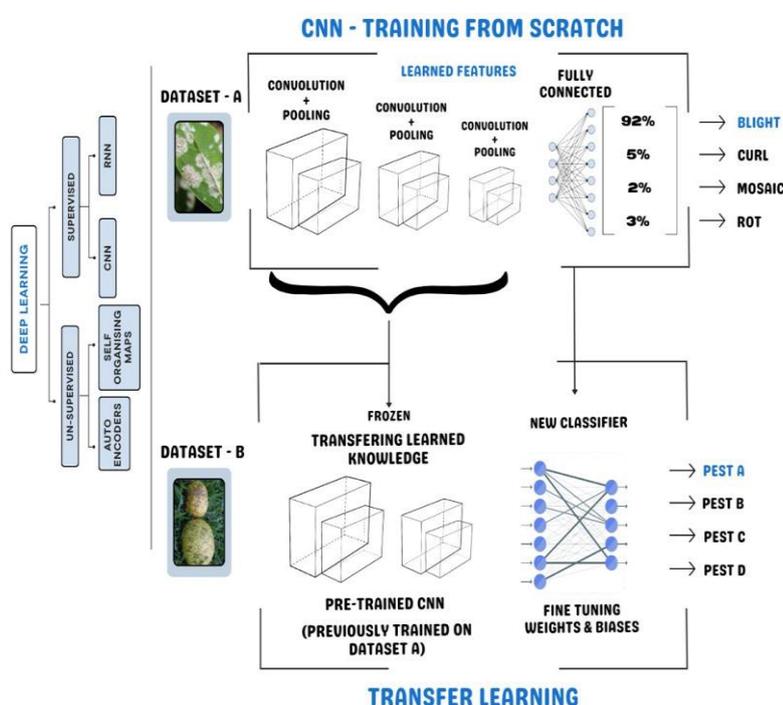


Figure 8 shows the architecture of training CNN from scratch and using the same CNN to train another model using Transfer Learning.

Vinay Kukreja [36] improved CNN performance with data augmentation and pre-processing, achieving an overall accuracy of 89.1% on 150 original images, expanded to 1200 through data augmentation. Oumayma Jouini [37] used transfer learning with ten CNN-based models to classify healthy and infected images. Mobile-Net stood out with a 95% test accuracy for real-world images on a wheat farm. M. Vengateshwaran [38] utilized Chaos theory, Faster R-CNN, Firefly algorithm, Otsu threshold segmentation, and K-Mean clustering for rice leaf disease detection. Fuzzy C Mean and K-Mean clustering achieved an overall accuracy of 98.72%. Santhoshkumar [39] suggested the PLDP Net-RF model for disease classification with a maximum accuracy of 96.21%. A pre-trained CNN model for deep convolutional

features and machine learning ensemble models to classify leaf diseases. The accuracy achieved was 95.8%. Shanwen Zhang [40] introduced GPDCNN for cucumber disease recognition, outperforming other models with an average recognition rate of 90%. GPDCNN showed convergence at around 60,000 iterations, while other models required more than 90,000. The limitations of CNNs have been addressed using recurrent neural networks (RNN), particularly long short-term memory (LSTM). Transfer learning was discussed, highlighting models like VGG16 and ResNet50 [41].

Table 3: Abstract of the CNNs employed in PDD

| REFEREN<br>CE | ARCHITECTU<br>RE<br>DESCRIPTIO<br>N                                      | DATASET<br>S<br>SOURCE         | LAYERS<br>&<br>FUNCTI<br>ON                                  | FE<br>TECHNIQ<br>UE                                 | RESULT<br>ANALYSIS              |                              |
|---------------|--|--------------------------------|--|---|---------------------------------|------------------------------|
|               |  |                                |  |   | Accura<br>cy &<br>precisio<br>n | Recall<br>&<br>F1            |
| [28]          | Tomato DD and classification using a CNN LVQ Algorithm.                  | 500 images from PVD.           | ReLU   | CNN performs FE, resulting in 500 feature vectors.  | 86%                             | 0.98 & 0.975                 |
| [30]          | CNN, ResNet, Inception V3, Explainable AI, LIME, Grad-CAM                | PVD                            | Seven types, Adam optimizer, ReLU, categorical cross-entropy | Grad-CAM  | 99.2% & 95.46%                  | RMSE – 0.015 & MAE – 0.012   |
| [36]          | Citrus DD using CNN, cross-entropy, and SGD                              | Internet                       | 64, ReLU   | SGD optimizer                                       | 89.1%                           | –                            |
| [39]          | A better CNN and random forest-based PLDP Net-RF model in apple leaf DD. | ImageNet & PVD                 | 15   | Random forest classifier and Conv layers perform FE | Acc - 96.21%<br>Pre - 96.66%    | Recall - 96.54 & F1 - 96.53% |
| [40]          | Global pooling dilated convolutional                                     | Camera, industrial demonstrati | 5, ReLU  | Automatic FE (SGD)                                  | 90%                             | –                            |

|      |   |                        |                  |  |                            |                               |
|------|---|------------------------|------------------|--|----------------------------|-------------------------------|
|      | neural network (GPDCNN) for PDD.  | on area, China         |                  |  |                            |                               |
| [42] | Ensemble pre-trained DCNN VGG-16, VGG-19, and Xception model for PDD.   | Kaggle                 | –                | Pre-trained DCNN, KNN, Multi-class LR, RF, XGBoost.                  | 95.8%                      | 0.91 & 0.92                   |
| [44] | Deep CNN for PDD  | 54,305 images from PVD | Nine layered CNN | Deep CNN   | 96.46%                     | 0.9989 & 0.9815               |
| [49] | Paddy leaf DD using DNN, PCA, and BFO-DNN.  | HD camera & PVD        | –                | FE - PCA & BFOA algorithm<br>Segmentation – K-means                  | 98%                        | Cross Entropy loss - 0.000209 |
| [60] | VGG19 for 24 sorts of diseases and pest detection and fertilizer recommendation chatbot   | Real field images      | –                | K- means cluster and random Forest classifier                        | 95%                        | –                             |
| [67] | Banana foliar DD using GLCM texture features and DTCWT  | DSLR, Kerala, India    | –                | FE - HOG, SIFT, SURF and BRIEF<br>Classification – KNN, SVM, NB, PNN | Acc - 95.4%<br>Pre - 93.2% |                               |
| [69] | Disease grading using CV and Fuzzy logic, Fuzzy Inference System (FIS) has been formed to grade the leaf diseases into different classes. | Dataset (Internet)     | –                | GLCM matrix & k-means segmentation                                   | –                          | –                             |
| [72] | SLIC-SVM-based saliency map extraction  | Tea plantation         | –                | GLCM algorithm   | Acc - 98.5%,<br>Pre -      | F1 - 98.6%<br>Recall -        |

|  |    |  |  |  |        |        |
|--|----|--|--|--|--------|--------|
|  | of |  |  |  | 96.8%, | 97.7%, |
|--|----|--|--|--|--------|--------|

Piyush Singh[43] proposed an end-to-end framework for identifying coconut tree diseases, leveraging k-means clustering segmentation and pre-trained models like MobileNet. Geetharamani G [44] introduced a nine-layered Deep CNN for plant leaf disease identification, achieving a classification accuracy of 96.46% through various enhancement techniques. AlexNet, VGG16, Inception-v3, and ResNet were the next best models. Table 3 depicts the overview of the various CNN techniques employed in plant disease detection and in the Figure 9 shows the graphical representation of CNN models and accuracies.

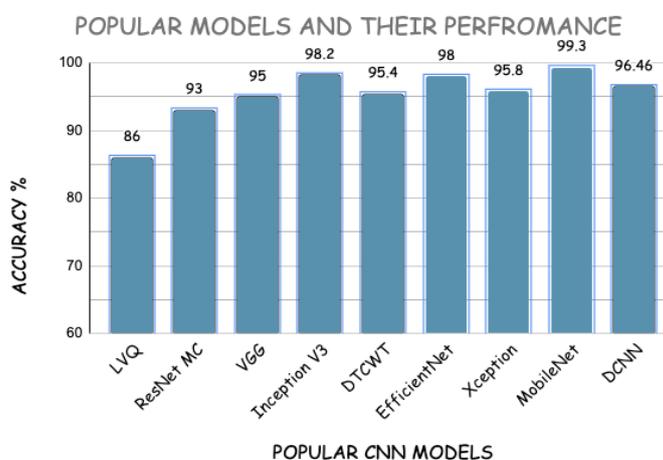


Figure 9: CNN models and accuracies

5. RQ5: Which image processing (IP) and feature extraction methods are chosen from deep learning algorithms?

Machine learning algorithms have made significant strides in understanding image data, resembling how our brains interpret visuals. These algorithms find application in various domains, from facial recognition on our smartphones to automating tedious tasks, powering self-driving cars, and much more. However, for machine learning algorithms to perform effectively, they require substantial amounts of high-quality data for learning and making accurate predictions. Therefore, ensuring that images are appropriately edited, tagged, and curated for machine-learning image processing is crucial. This is where Computer Vision (CV) comes into play. Computer Vision is a field dedicated to enabling machines to comprehend and interpret image data. It facilitates the identification of objects within images by employing techniques like pattern recognition. Machine learning subsequently trains the system to detect and adapt to pattern changes. Pattern recognition is fundamental to various applications, including computer-assisted diagnosis, character recognition, image classification, handwriting recognition, and more. A computer vision and deep learning-based approach for diagnosing plant diseases using smartphone images. Their algorithm achieved a 99.35% accuracy rate on a dataset of 54,306 photos of damaged and healthy plant leaves.

They automated the segmentation process and emphasized that their method complements existing disease diagnosis methods. Zahid Iqbal et al [11] proposed a deep learning approach using convolutional neural networks (CNN) based on well-established deep learning techniques like GoogLeNet, OverFeat, AlexNet, VGG, and AlexNetOWTBn to classify leaf diseases. Their results showed that the AlexNetOWTBn model performed well compared to other methods. Hu Gensheng et al. [29] introduced a low-risk learning approach for identifying diseases in tea leaves using deep learning models, including conditional deep convolutional generative adversarial networks (C-DCGAN) and VGG16. They addressed the challenge of complex backgrounds in field-captured images by employing a Support Vector Machine (SVM) to separate disease spots. Overfitting was mitigated using C-DCGAN, which augmented the dataset by generating more training images. The generative networks were utilized to create target samples, and the augmented data was then used to train a VGG16 model, achieving a 90% accuracy in classifying four disease classes. VGG16 was preferred due to its faster training times and efficient architecture with smaller convolution kernels and fewer parameters. Thomas S et al. [32] explored the emerging applications of hyperspectral imaging in Plant Disease Diagnosis (PDD). They noted that human vision only captures a limited spectrum of electromagnetic radiation, with many wavelengths beyond the visible spectrum. Hyperspectral imaging (HSI) was introduced to analyse a broader spectrum of light. The method divides the light striking each pixel into various spectral bands, providing more detailed information about scanned objects. Lin Yuan and their team demonstrated the use of HSI for detecting tea plant anthracnose, which significantly expanded the spectral sensitivity and allowed the identification of diseases.

Table 4: Overview of DL & IP models used in PDD

| REFERENCE | METHODOLOGY DESCRIPTION                     | DATASETS              | SEGMENTATION | LAYERS & FUNCTION     | RESULT ANALYSIS      |             |
|-----------|---|-----------------------|--------------|-----------------------|----------------------|-------------|
|           |   |                       |              |                       | Accuracy & precision | Recall & F1 |
| [2]       | AlexNet from scratch and TL based GoogleNet | PVD                   | k-means      | 7&22, ReLU AF         | 99.35 %              | —           |
| [29]      | VGG16 DL model, C-DCGAN for                 | Tianjingshan National | SVM          | WGAN-GP Loss Function | 90%                  | —           |

|      |  |   |                               |  |   |                            |
|------|--|---|-------------------------------|--|---|----------------------------|
|      | tea leaf DD.   | Park  |                               |  |   |                            |
| [30] | Transfer learning-based Inception V3 and ResNet-9 and XAI tools such as LIME and Grad-CAM for PDD. | PVD is divided into 38 classes.                               | Batch NormalizationSoftMax    | ReLU Activation Function with an adam optimizer. | inception V3 – 98.18 % & ResNet – 99.16 % | RMSE – 0.015 & MAE – 0.012 |
| [31] | 3 TL methods fine-tuning, Deep CORAL, and DDC for rice DD using Hyperspectral images.              | China Rice Research Institute and Zhejiang Bedokno n Seed Co. | –                             | 6, ReLU AF                                       | 88%                                       | –                          |
| [34] | AlexNet algorithm to classify the plants' leaves and categorize them into healthy and diseased.    | Kaggle & Github   | KMC, Otsu Threshold Algorithm | –  | 97.5%                                     | –                          |
| [35] | GoogLeNet Inception structure and Rainbow concatenation based Apple DD                             | (ALDD) Apple Experiment St of Northwest A&F Uni               | K-means                       | SGD to minimize the loss function                | –   | mAP – 78.80 %              |
| [36] | (DL) & CNN methodology for the automated diagnosis and   | 128 – DSLR Pakistan   | –                             | 4 layers, pooling, ReLU AF                       | 89.1%                                     | –                          |

|       |  |                                   |  |                                       |                                    |                       |
|-------|--|-----------------------------------|--|---------------------------------------|------------------------------------|-----------------------|
|       | categorization of citrus DD.   |                                   |  |                                       |                                    |                       |
| [43]  | Coconut DD using 2D-CNN and various TL-based Xception, Inception, VGG DenseNet, MobileNet, Inception, ResNetV2, and NASNetMobile models. | DSLR camera, TANUV AS, Chennai    | K-means Clustering, Watershed, Thresholding segmentation | 42 layers, ReLU Softmax AF            | 96.94 %                            | –                     |
| [47]  | Custom CenterNet framework with DenseNet-77 as a base network for deep feature extraction in PDD   | PVD                               | –  | ReLU                                  | 99.982 %                           | 0.98                  |
| [50]  | LASSR model composed of two CNN models for PDD   | DS-A & DS-B, Japan from 2015-2019 | –  | 115, Leaky ReLU(LReLU) SoftMax AF, BN | 98.32 % & 97.42 % in testing & val | –                     |
| [70]. | Time-efficient PDD using IP and CNN architecture.  | PVD (potato, tomato, bell pepper) | –  | Dropout, ReLU.                        | ACC - 94% (Training loss - 0.05%)  | Validation loss 0.36% |

|      |  |                     |   |                            |                 |   |
|------|--|---------------------|---|----------------------------|-----------------|---|
| [73] | 3 networks of different depths, VGG-16, Inception v3 and ResNet-101 as the base networks for the T-CNN for PDD | PVD and PlantDoc DS | – | VGG – 16, Softmax AF, ReLU | 99.99 % & 99.7% | – |
|------|--|---------------------|---|----------------------------|-----------------|---|

Piyush Singh et al. [43] introduced an end-to-end framework for identifying diseases and pest infections in coconut trees. They used deep 2D-Convolutional Neural Networks (CNN) for disease anticipation and fine-tuned pre-trained CNN models for image classification. Their empirical study favored k-means clustering segmentation and reported high accuracy and Kappa values. Gauri Shankar Singh et al. [45] suggested a tool for farmers to detect plant diseases by scanning leaves or submitting leaf images. They employed convolutional neural networks, including VGG-16, training and experimented with optimizers like SGD, AdaGrad, and RMSprop. Namrata, Nikitha, et al. [46] used a convolutional neural network based on VGGnet16, Stochastic Gradient Descent (SGD), and Adadelta to distinguish between healthy and diseased leaves. They resized image datasets to 100x100 to expedite. DenseNet-121 and Inception and used the V3 algorithm to scale images and gather data based on color. VGG-16, with its 16 convolutional layers, was the preferred choice for image classification. DenseNet-121 was also used, and Inception V3 with 48 layers was applied to identify different potato and tomato diseases using various segmentation techniques. Results showed high training and validation accuracies for these models. Table 4 summarizes various DL and IP techniques employed along with their performance in an organized way.

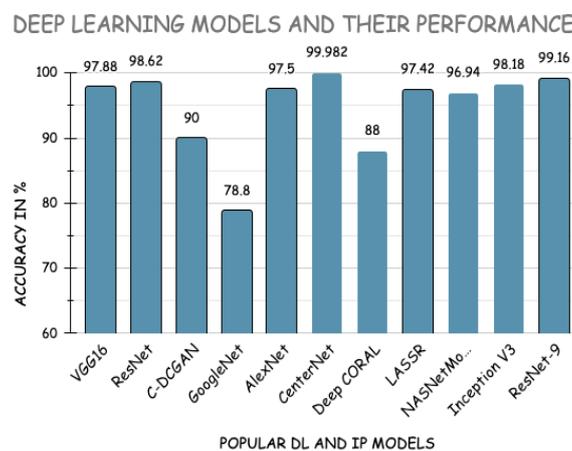


Figure 10: DL IP models and their Accuracies

Waleed Albattah et al. [47] introduced a custom CenterNet framework with DenseNet-77 as the base network to improve the accuracy of plant disease detection and classification. They used a one-stage object detection framework and customized CenterNet to achieve maximum accuracy. Their approach was evaluated on the PlantVillage dataset containing many crop disease images, achieving high mean IOU and mAP scores. Quan Huu Cap et al. [48] proposed LeafGAN, an attention-based image-to-image translation system for data augmentation in plant disease diagnosis. LeafGAN generated a wide range of diseased images from healthy ones. This technique addressed overfitting issues and significantly improved disease diagnostic performance compared to baseline methods. LeafGAN models were trained using leaf images from different sources. Aakrati Nigam et al. [49] used image processing and classification techniques to identify various leaf diseases. They captured images of different paddy leaves and processed them by transforming color models, conducting segmentation, and using feature extraction techniques. Their classification approach, which employed the BFOA-DNN model, improved the detection rate and reduced entropy loss, achieving effective multi-category disease recognition. Figure 10 shows a graphical representation of various DL techniques that used IP and their performances in terms of accuracy percentages. Quan Huu Cap et al. [50] introduced Leaf Artifact-Suppression Super-Resolution (LASSR), a technique designed for diagnosing leaf diseases. LASSR used CNN models to separate super-resolved (SR) images from high-resolution (HR) images. It addressed image artifacts and significantly improved disease detection performance. LASSR also featured an artifact removal module (ARM) for eliminating artifacts during training, enhancing the quality of SR images. Hamdani et al. [51] developed a new approach for oil palm leaf disease detection, employing color space analysis, segmentation using K-means clustering, feature extraction, and artificial neural network (ANN) classification. Their approach achieved high sensitivity, specificity, and accuracy in distinguishing healthy and diseased leaf classes. Navneet Kaur et al. [52] developed an ensemble classification approach using various feature extraction algorithms for classifying diseases in bell peppers, potatoes, and tomatoes. The ensemble classifier achieved high accuracy, precision, and recall across different disease categories. These studies highlight the diverse applications of deep learning, hyperspectral imaging, and image analysis techniques in plant disease diagnosis and detection.

*6. RQ6: How does IOT-assisted technology help in PDD and management, and what is auto-encoder hype?*

Table 5: Overview of Various IoT Hardware Employed in PDD

| AUTHOR | MODEL DESCRIPTION  | HARDWARE AND SENSOR  | PERFORMANCE METRICS |          | ADVANTAGE  |
|--------|--|--|---------------------|----------|--|
|        |  |  | Accuracy            | F1 Score |  |
| [53]   | Automatic insect pest monitoring (trap) based on EdgeAI and CNN  | OpenMV Cam STM32H7 Plus bases MCU, STM32H743II ARM Cortex, OV5640 imaging sensor.  | 70%                 | –        | The power consumption of MCU-based sol is multiple times less than that of RPi-based sol.  |
| [54]   | Deep learning YOLOv3 for image recognition, real-time agricultural meteorology, and PDD systems on mobile applications.  | Single Shot MultiBox Detector. 6 environmental sensing modules: Arduino Nano, GY-30, dirt, DHT22, BMP180, DS3231, and LORA module. | 90%                 | –        | Farmers were immediately informed of the pests' position and distribution using environmental sensors, allowing for precise pesticide application. |
| [55]   | IoT is a solar-powered innovative farming system with CNN for crop disease prediction. The watering process is tracked by an IoAT app, which also aids in evaluating crop photographs from | ESP-8266 microcontroller, soil moisture, temperature, humidity solar sensor nodes (DHT11 + NodeMCU), and camera sensors.           | 99.24%              | –        | The suggested system is more energy-efficient than existing methods because a solar panel powers the solar sensor node.                            |

|      |   |   |             |                |   |
|------|---|---|-------------|----------------|---|
|      | the IoT ThingSpeak cloud to identify potential diseases.  |   |             |                |   |
| [56] | UAV-based visually acoustic early Pest DD Transfer learning based YOLOv5 model.   | DJI Mini 3 Pro, CMOS camera, Rode Videomic Me Cardioid Mini- Shotgun mic, Visual and Acoustic sensors       | Pre – 92.6% | Recall – 84.3% | The current design can completely cover up to 12,500 m <sup>2</sup> /hr for less than \$1000 per unit, impact on in-field tracking of pest species, and can also be applied to ecological management restoration. |
| [66] | The apple leaf DD and the creation and testing of a robot that can irrigate, fertilize, and apply pesticides to agricultural areas.   | Raspberry Pi, VCC1, VCC2, soil moisture sensor.   | mAP – 78.8% |                | Garden, horticultural, and agricultural lands can all be irrigated with this method. Because of this, this automation system is more cost-effective and efficient than other kinds.                               |
| [74] | When a codling moth is found, the system takes a picture of the trap, preprocesses it, crops each insect for classification, and then notifies the farmer using near-sensor neural network algorithms and | It uses a Raspberry Pi3 board, Intel Movidius Neural Compute Stick, LPWAN, and long-range LoRaWAN protocol. | 94.38       | Recall= 92.6   | Despite not using ultra-low power microprocessors or microcontrollers, the suggested system's short-duty cycle ensures that its average power consumption is relatively low.                                      |

|  |        |  |  |  |  |
|--|--------|--|--|--|--|
|  | VGG16. |  |  |  |  |
|--|--------|--|--|--|--|

Amin Kargar et al. [53] introduced a cost-effective smart insect trap to identify harmful bug species affecting fruit quality. They utilized a Microcontroller Unit-based edge device (MCU) with a low-cost camera for image acquisition and processing. The device employed a Convolutional Neural Network (CNN) model and lightweight image analysis technique for insect identification and categorization. The model achieved a stable accuracy of around 97% after 15 epochs, with a classification accuracy above 70% for the Brown Marmorated Stink Bug (BMSB). Ching-ju chen et al[54] merged artificial intelligence, picture recognition (YOLOv3), AIoT technology, environmental sensors, and the Internet of Things (IoT) to identify *Tessaratoma papillosa*. They used Long Short-Term Memory (LSTM) to collect environmental data and obtained a test accuracy of 90%. Image processing techniques were applied to 687 photos of adult *Tessaratoma papillose*, and data augmentation was used to enhance the YOLOv3 training samples. Their compact embedded platform used an Arduino Nano and various sensors to monitor environmental data. The model achieved an accuracy (mAP) of 92%.

Various advantages of IOTs and their performances are summarized in Table 5. Venkanna Udutalapally [55] proposed a solar-enabled smart agricultural system using images from the PlantVillage collection for crop disease prediction. They utilized color gamut conversion and designed a solar sensor node to monitor environmental data, soil moisture, and crop images. The system achieved high energy efficiency due to solar panel power. Soil moisture values helped automate irrigation, and crop images were processed and stored in the ThingSpeak cloud. The plant disease prediction framework achieved an impressive accuracy of 99.24%. Ryan Ruien Zhang et al. [56] developed an innovative visual-acoustic method for pest detection using unmanned aerial vehicles (UAVs). They introduced the Pest Early Detection System (PEDS-AI), which combines visual and acoustic data for species detection. The system's dual signal processing approach addressed low signal-to-noise ratios, and deep learning techniques were applied to identify pests. The design was cost-effective, and the model achieved high precision and recall rates. C. Cathrin Deboral et al. [57] proposed a Plant Disease Diagnosis (PDD) prototype using IoT. Their model allowed for real-time data management, weather forecasts, and soil analysis, aiding farmers with nutrient and moisture delivery. Sensors collected temperature, moisture, humidity, soil nutrients, and disease status data. Arduino and embedded software were used for system implementation. Data on soil conditions were transmitted to a website, and the system's IoT capabilities allowed for disease prediction based on soil data. The model achieved an accuracy of 99.24%. Naveen B et al. [58] designed a robot for pesticide application. The robot had stages for seed dispersal, obstacle identification, and pesticide application. The robot utilized sensors, a microcontroller, and an Arduino platform for navigation and pest detection. It also integrated an ultrasonic sensor for disease detection. Hyeon O Choe et al. [59] used three cameras for a pest detection system that automatically rotates when pests are collected, reducing manual

intervention. Sensors were employed to monitor environmental conditions, and a management module processed and transmitted image data. The power source included both direct wire charging and solar battery charging. The system employed different traps, including sticky traps, pheromone traps, and enticing lamps, to capture pests.

*7. RQ7: How can the optimization of the loss function between training and test datasets be achieved while simultaneously mitigating the problem of overfitting?*

When a statistical model fails to make accurate predictions on test data, it is considered overfit. Overfitting occurs when a model starts to learn from the noise and inaccuracies in a large dataset, resulting in high variance when tested. The model needs to be more detailed and noisier to identify the data effectively. An overfitted model has low bias and high variance, and the risk of overfitting increases as the model is trained more extensively. Overfitting is a fundamental challenge in supervised learning. In selecting research papers on deep learning approaches to mitigate overfitting, 18 papers were initially identified. Eventually, six papers were chosen for analysis.

A loss function assesses how well a neural network model trains data by measuring the disparity between predicted and target output values. The objective is to minimize this difference during training by adjusting hyperparameters, such as weights and biases as per the below equation.

$$J(w^T, b) = \frac{1}{m} \sum_{i=1}^m L(\hat{y}^{(i)}, y^{(i)})$$

(8)

MSE, or Mean Squared Error, is a commonly used loss function that calculates the average squared deviations between desired and predicted outputs. On the other hand, MAE, or Mean Absolute Error, determines the average of absolute disparities between target and predicted outputs as per the below equation.

$$MSE = \frac{1}{n} \sum_{i=1}^n L(y^{(i)}, \hat{y}^{(i)})^2$$

(9)

Dropout is a technique to mitigate overfitting by randomly deactivating hidden neurons during each training iteration. Rectified Linear Units (ReLU) are used to introduce non-linearity. Normalization methods maintain the input data distribution throughout training to reduce internal covariance shifts.

Rakesh S [30] suggests addressing overfitting using data augmentation methods involving operations like mirroring and image rotation. introduces digital image processing techniques, including rotation, mirror symmetry, and intensity disturbance, to create diverse training images, preventing overfitting and enhancing generalization. Vinay Kukreja et al. [36]

employ dropout to reduce overfitting. It involves randomly setting hidden neurons' outputs to zero during training iterations, helping to optimize the cross-entropy loss function. Oumayma Jouini et al. [37] combat overfitting with data augmentation techniques for CNN models. Their MobileNetV2 model achieves high training accuracy without overfitting. Shanwen Zhang et al. [40] use global pooling, or Global Average Pooling (GAP), to reduce overfitting by reducing parameters and dimensions while improving generalization. In the work of ching-ju chen et al. [54], stochastic gradient descent (SGD) is employed as the learning algorithm. It updates weight parameters using the negative gradient and parameter deviations to minimize the error function. The learning rate ( $\alpha$ ) is set to 0.0001, and SGD is used to calculate the loss function's gradient. The training dataset's gradient is updated in epochs as per the below equation,

$$\theta_{l+1} = \theta_l - \alpha \nabla E(\theta_l)$$

(10)

Poonkuzhali Ramadoss et al. [60] utilize augmented and actual image samples to train their CNN algorithm. Various augmentation techniques, including cropping, were found to improve CNN accuracy and mitigate overfitting. Mohit Pankaj et al. [61] experimented with optimization techniques, including RMS-Prop and Adam, to decrease loss percentage and mitigate overfitting. Waleed Albattah et al. Ümit atila et al. [62] mention employing early stopping during training to identify the optimal epochs for models' starting points and avoid overfitting.

### **Conclusion**

Early detection of plant diseases is paramount for maximizing plant productivity and ensuring high-quality yields in today's agricultural landscape. This paper provides a comprehensive overview of various methods to identify and classify plant leaf diseases. The findings emphasize the efficiency of the transfer learning strategy for disease categorization. The critical facets of disease detection, accuracy, and timely identification are highlighted. The forthcoming phase of this research will prioritize the development of advanced algorithms tailored for the precise detection of afflicted leaves. It is imperative to give due attention to influential factors affecting plant disease detection, including dataset characteristics (classes and size), learning rate, and lighting conditions, among others, to achieve optimal accuracy.

### **Data Availability Statement**

The data that supports the findings of this study are available within the article in the reference section.

### **Author Contributions Statement**

All authors share equal contributions.

### **Disclosure of interest**

The authors declare that they have no known competing interests.

**Declaration of funding**

The authors declare that they have no sponsorship or funding.

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