# **Chapter Two: Literature Review**

# **2.1 Introduction**

This chapter presents a comprehensive review of existing research, systems, and practices related to plant disease detection, with a particular focus on the role of technology- especially smartphones- in facilitating these processes. The purpose of this review is to establish a solid foundation for understanding the current state of work in this field and to identify the limitations and gaps in existing systems that our proposed solution aims to address. By examining previous studies and technologies relevant to plant disease detection applications, this chapter not only highlights the progress made so far but also provides the conceptual and technical framework that supports the development of our proposed system.

# **2.2 Literature Review**

The author of [1] conducts a comprehensive survey of deep learning methods for plant disease detection. The authors aggregate studies utilizing CNN architectures (including AlexNet, VGG, ResNet, and MobileNet). This review provides readers with a thorough overview of how deep learning is applied in plant disease identification.

The review employs an analytical and comparative approach. It contrasts various studies' outcomes and shows that CNNs yield significantly higher accuracy than previous techniques. The paper also details the datasets, training methods, and evaluation metrics used.

In [2], a machine learning technique for plant disease detection is developed, aiming to provide a cost-effective, automated diagnostic tool for farmers. The authors utilize a Random Forest classifier. The workflow consists of four stages: image preprocessing, feature extraction (using Histogram of Oriented Gradients, Hu moments, Haralick texture features, and color histograms) to form feature vectors, followed by model training.

Images of 160 papaya leaves, both healthy and diseased, were used for training. Compared to other methods such as SVM and Logistic Regression, Random Forest performed the best, achieving an accuracy of nearly 70%.

Overall, the article demonstrates that classic machine learning methods, such as Random Forest, offer a basic approach; however, their accuracy is lower than that of deep learning.

The performance of machine learning and deep learning methods to determine which approach is better at identifying plant diseases is compared [3]. They used the PlantVillage dataset and trained both classical machine learning methods (SVM, Random Forest, kNN) and CNN architectures on it. According to the results, CNN achieved an accuracy above 95%, while machine learning models did not reach this level.

In contrast with others in [4], they have compared the performance of various deep learning models, such as AlexNet, VGG, ResNet, Inception, and DenseNet, in plant disease detection.

They used PlantVillage and crop image data, pre-processed it, and then trained the models. The results showed that ResNet and DenseNet achieved the highest accuracy, and transfer learning was more effective for small data sets.

Team [5] studies how image recognition models can help identify leaf diseases in crops with deep learning. They pointed out that plant diseases can harm both crop yields and food quality. Since traditional methods are slow and need experts, they tested pre-trained CNN models like VGG-16, ResNet-50, Inception V4, and DenseNet-121 to see which worked best.

They used the PlantVillage dataset, which contains over 54,000 leaf images (38 categories of diseased and healthy leaves). They processed the images (resizing, normalizing, and data augmentation) and then tuned the hyperparameters of the models during training. The results showed that all models had high accuracy, but DenseNet-121 performed the best, achieving almost perfect accuracy (99.81%).

The study to compare advanced deep learning models for plant disease detection was condacted in [6] that their goal was to find a system that would be fast, accurate, and useful in agriculture. They used popular CNN models such as VGG16, Inception V4, ResNet (50, 101, 152), and DenseNet-121. All models were fine-tuned with pre-trained weights from ImageNet and tested on the PlantVillage dataset.

They preprocessed the dataset (resized and normalized) and divided it into training, validation, and testing parts. During training, they modified the last layers and calibrated them using SGD. The results showed that all models had high accuracy, but DenseNet-121 performed the best (99.75% accuracy). This model required less computational power than the others and did not suffer from overfitting. In contrast, VGG16 was the weakest.

As stated in [7] they investigated CNN-based plant disease detection. Their goal was to show how accurately CNN could detect plant diseases.

They used the PlantVillage dataset, which contains over 50,000 images. They tested the AlexNet and GoogLeNet models and achieved an accuracy of up to 99.35%.

Explain a method for identifying plant diseases based on deep learning, as pointed out in [8]. The researchers used the PlantVillage dataset, which contains thousands of images of healthy and diseased leaves. They performed pre-processing and augmentation of the images and then trained a disease detection model using convolutional neural networks (CNNs). The results showed that the CNN models achieved an accuracy of more than 98% in identifying plant diseases.

In line with findings from [9], the process of diagnosing agricultural plant diseases is improved using convolutional neural networks (CNNs). Traditional diagnostic methods are labor-intensive, expert-dependent, and impractical for large farms. To address this, CNNs are trained using healthy and diseased leaf images from the PlantVillage dataset.  
Preprocessed images were augmented to enhance resilience, and models were trained on several crops and diseases. Findings were higher achievements in classification accuracy as compared to the conventional diagnostic approaches. This indicates that CNNs can be dependable instruments with regard to precision agriculture.

According to [10], they tackle the subject of sustainable agriculture in the context of climate change and strive to enhance crop monitoring algorithms by using machine learning and remote sensing. Using several accumulating spectral and hyperspectral satellite data images/UAV data, and combining with ML algorithms, they identified the indicators of crop growth.  
It was demonstrated that the trained models strongly performed at aiming stress on plants, crop type classification, and yield prediction, offering high accuracy and scalability compared with traditional methods of analysis.  
The main drawbacks are that these methods need large, high-quality datasets, which are often hard to get in developing regions. They are also sensitive to the environment, can have sensor inconsistencies, and require expensive computing. Most tests were done in controlled settings. Future work will focus on using bigger datasets, adding more field measurements, and creating cheaper solutions to make the technology more accessible.

Selected a specific crop, apple trees, and studied them in particular as they are susceptible to the leaf disease [11]. They observed that the conventional means of detecting those problems were slow and at times inaccurate, particularly in situations when the leaves contained minute spots or were photographed in chaotic, real-world conditions. As a solution, they scaled up the Faster R-CNN model and used it with Res2Net and a Feature Pyramid Network (FPN) to make the system capable of locating finer details in leaf  
images.  
Unlike other works, what is outstanding about their work is that they did not use clean lab images. Rather, they made up their own data, AALDD, stuffed with thousands of actual  
photographs of the leaves of apples in orchards. They also implemented methods such as the RoIAlign that helped to sharpen the capability of the model in feature location and soft-NMS to minimize errors when disease spots were overlapping.  
Results were encouraging: for diseases such as powdery mildew and mosaic, this model reached more than 90 percent accuracy, and it demonstrated that it can also deal with real farming conditions. Nevertheless, it had certain challenges. This model did not cope with rust disease, which appears as extremely small and fragile spots, and its speed (approximately 12  
frames per second), which is too slow for real-time use in the field. While this is a limitation, the research still marks important progress. It shows that deep learning can make disease detection easier for farmers if future models become faster and more efficient.

A different category of devotees shifted their focus to cherry production in Chile, an important high-value crop where precise predictions of harvest are worth billions of dollars. Their designed system was based on the Faster R-CNN model with the help of Inception V2 and made to recognize cherries on field images at varying lighting conditions and maturity stages [12].  
The error rate of the forecasting was halved, the success rate of the older techniques being at only 25 percent of the forecasting error rate previously. Farmers themselves could now make  
very reliable forecasts of the amount of yield they would get, which helped them to organize labor, storage, and market plans more predictively.  
Naturally, there were hindrances. The model was more difficult to recognize smaller cherries, and the model would occasionally lead to errors, whereby leaves or other objects made contact with the images. Nevertheless, the findings reveal that deep learning would not only transform agricultural forecasting but also the forecasting of most crops, in addition to cherries. The paper identifies the ways AI can add real wealth to the agricultural sector through more  
accurate predictions and less uncertainty.

Similarly, [13] discovered bacterial diseases through an analysis of the images of the leaves of cherries. They did not create a model; instead, they applied DarkNet-19, a pre-trained deep learning model, to extract features. These characteristics were then injected into various machine learning methods, which were the Support Vector Machine (SVM), Linear Discriminant Analysis(LDA), and K-Nearest Neighbor (KNN).  
The sample consisted of 1,906 images, and it included healthy, mildly diseased, and severely diseased. These findings were promising: the system was capable of identifying bacterial  
disease at about 88 percent, although the highest accuracy was achieved by SVM. This stood out because it was not only possible to draw the line between a healthy condition and a sick one, but also to define the various levels of disease severity, which could be important in a quick response to it.

This perspective is further reinforced in [14], the identification of cherry bacterial leaf diseases. The focal point, this time, was the application of deep features made by DarkNet-19 together with conventional machine learning classifiers like SVM, KNN, and LDA. The dataset was identical in size to that used previously- 1,906 leaf images categorized as healthy, mildly diseased, and severely diseased.  
The strategy was actually highly successful, as it was able to detect disease severities with an accuracy of approximately 88 percent, and SVM outperformed it once again. This lesson was that with the standard ML classifiers and deep learning to extract features, the system was capable of providing reliable disease detection without an overly complex architecture.  
The authors recognized that the outcome would be given a higher quality of preprocessing and tuning, but on their side, they also indicated the extent to which such a system could be of  
significance in practice. The timely detection of the disease gives the farmers an earlier opportunity to do something and save their yields and enhance their productivity. They indicated that in the future, they might increase the dissemination of the system to a larger number of plant species, disease types, and possibly even modules that could interact with the treatment plan and diagnosis.

As noted in [15], they develop four deep learning models: a custom “Vanilla” CNN, and three other models that improved via transfer learning from pre-trained architectures (VGGL6, MobileNet, and AlexNet).  
They created a data set of grape leaf images, which was pre-processed through (cropping, flipping), to balance the classes. The models were trained and evaluated on the dataset. Finally, they created an ensemble models that predicted all four models by using an average voting method to boost accuracy.

The meteorological data of (temperature, humidity, rainfall)and the historical disease occurrence records are collected [16].  
They used MATLAB for data preprocessing, which included outlier detection and visualization with Principal Component Analysis. They have built and compared several prediction models. The best-performing model was a pruned decision tree that used rules based on weather parameters and the month of the year to predict disease risk. This paper predicts the risk of two cherry fruit diseases by using weather data and data mining techniques, rather than image analysis.

The challenge of the class imbalance in the plant disease dataset is addressed by proposing three novel methods based on the DenseNet-121 architecture to improve the recognition of six types of apple leaf diseases. In [17], they used standard multi-class classification with a cross-entropy loss function, and they proposed three alternative approaches:(Regression, Multi-label Classification, and Focal Loss).

As revealed in [18], they aim to develop a highly accurate yet computationally efficient model for grape leaf disease classification that can be deployed on mobile devices with limited resources.   
The authors chose the lightweight CNN architectures (ShuffleNet V1 and V2) as their backbone. To boost accuracy without a significant computational cost, they integrated a Channel-wise Attention (CA) mechanism into these networks. This one allows the models to focus on the information features in the image. They tested their improved models on a grape leaf dataset and compared their performance and size speed against other models like AlexNet and MobileNet.

As proposed in [19], an automated system for classifying disease in grape leaves using an ensemble of deep learning models. The goal of that is to improve accuracy and reduce overfitting compared to using individual models.  
And they use an ensemble learning approach that combines three pre-trained convolutional Neural Networks (CNNs): VGG16, VGG19, and Xception.  
And the data set they used was the publicly available PlantVillage dataset, specifically the 4062 images of grape leaves.

A real-time object detection system to identify and locate multiple diseases on a single apple leaf image in complex field conditions was developed in [20].  
The focus on real-time performance and handling small disease spots against complex backgrounds.  
They construct their own Apple Leaf Disease Dataset (ALDD) with 26,377 images from both laboratory and real-field conditions, which are manually annotated.  
They create a new Model Architecture that is INAR-SSD, which is trained on their own dataset, that is the ALDD dataset.

As explored in [21], creating a highly accurate yet lightweight and efficient model for classifying grape diseases makes it suitable for deployment on devices with limited computational resources.  
The proposed model (GLD-DTL) with a very small model size and a significantly larger output performed is larger than models like VGG19.  
They used the model of MobileNetV3, a model designed for mobile devices, as their base.  
They use data augmentation to balance the classes.  
The goal is to use a model that is both small in size and highly accurate.  
The model's performance is demonstrated on a cleaned and curated dataset. Its robustness to very noisy, low-quality field images is implied but not extensively tested.

As examined in [22], they implement a custom Convolution Neural Network (CNN) from scratch to classify four types of apple Leaf conditions, focusing on a simple yet effective approach.

The aim is to build a functional model without relying on pre-trained networks or complex architectures.  
They use a subset of the PlantVillage dataset containing 2,526 images. The model is trained from scratch using the Adam optimizer. And it identifies the dataset's artificial nature as the biggest drawback for real-world applications. Parameters like dropout, batch size, and train-test split ratio.

They develop a highly accurate and efficient image classification model for detecting grape leaf diseases using the lightweight MobileNetV2 architecture, aiming for potential deployment on resource-constrained devices in [23]. The primary goal is to demonstrate that a lightweight CNN like MobileNetV2 can achieve superior accuracy while maintaining computational efficiency.  
 They employ transfer learning with the MobileNetV2 model pre-trained on ImageNet. The top layers are replaced with custom layers for the 4-class problem.  
The external validation set was very small (20 images); a larger and more diverse external dataset is needed for a robust assessment of generalization.

As demonstrated in [24], they addressed the complex problem of detecting and localizing multiple diseases on a single leaf image, using an object detection approach, rather than standard image classification, which assumes one disease per image.  
The R-CNN models are trained to both classify the disease within each proposed region and predict the precise bounding box coordinates.  
The research aims to detect and draw bounding boxes around three grape leaf diseases (Black Rot, Black Measles, Isariopsis) and healthy leaves, even when they appear together in a single image. A key feature is the inclusion of a confidence value for each prediction.  
The R-CNN models are trained to both classify the disease within each proposed region and predict the precise bounding box coordinates.  
They compare three pre-trained networks (AlexNet, GoogLeNet, ResNet-18) as the backbone feature extractors within a Regions with Convolutional Neural Networks (R-CNN) framework for object detection.

# **2.3 Summary**

The literature review of the thesis on plant disease detection Application provides an overview of the existing literature on plant disease detection systems and Android-based mobile apps. This literature review examines 5 sources, including research papers, videos, and websites, to explore the development and impact of plant disease detection applications. various studies and journals were analyzed to address the significance of this issue.

Most existing studies on plant disease detection have demonstrated that deep learning, particularly CNN-based models such as ResNet, DenseNet, and MobileNet, can achieve very high accuracy using datasets like PlantVillage. However, these works are mostly limited to lab-controlled images, require large labeled datasets, and rarely focus on deployment for farmers. Unlike these studies, our project addresses these gaps by developing a lightweight mobile application for three key fruits (apples, cherries, and grapes) that not only detects diseases but also provides **localized treatment recommendations in Pashto/Dari**, making it more practical and accessible for farmers in Afghanistan.

# **2.4 References**

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