Comparative Analysis of Deep Learning Techniques for Automated Plant Leaf Disease Detection: A Comprehensive Survey

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Plant leaf disease detection in the early stages is very important for farmers to produce a better quantity and quality crop. Performing this task manually is very challenging and requires expertise in pathogens to detect them as early as possible and cure them with the right treatment. Automation in this industry is crucial in order to reduce manpower and treat plants at the ideal moment to avoid low recognition efficiency and poor dependability due to errors made by humans. There is extensive research happening to automize plant leaf disease detection and has received high accuracy on deep learning models to automate. The performance of various architectures such as VGG19, EfficientNet, MobileNet, and DenseNet used as across different datasets. Our analysis reveals that EfficientNet outperforms other models in terms of accuracy and MobileNet in terms of computational efficiency, making it suitable for deployment on both high-end and low-end devices. Still, there are many challenges to solve in this automation, like the cost of a high definition camera to capture plant leaf images and the computational cost to process the images. This paper concludes by discussing the challenges and opportunities for further research. The difficulties include developing more robust and precise image capture and pre-processing techniques, extracting more discriminative features, and creating more efficient and effective classification algorithms. Deep learning techniques, the development of mobile and web-based applications, and the integration of plant leaf disease detection with other agricultural technologies are all possibilities.

Keywords: Precision Agriculture, Machine Learning, Deep Learning, Computer Vision, Disease Identification, IoT (Internet of Things) in Agriculture, Sustainable Agriculture, Disease Monitoring.

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1 Introduction

Plants are an important resource for human life. About 30-35% of the crops grown in India each year are wasted because of pests. Plant diseases may cause severe agricultural loss, and traditional techniques of identifying plant diseases are sometimes time-consuming and inaccurate. Plant diseases that go unnoticed and untreated can have severe impacts on crop yields, the consequences include significant economic downturns and widespread scarcity of food. Finding and predicting plant diseases early is crucial to stopping them and managing them effectively [6]. Plant diseases can harm any part of a plant, from the roots to the leaves to the fruit, which can lower the amount and quality of crops produced. Leaves are an important part of plants to detect any early diseases in them and are shown visibly. However, new technologies, such as computer vision, deep learning, machine learning, and sensors, have the potential to revolutionize plant disease recognition. These technologies can make it faster, more accurate, and more efficient to identify plant diseases, which will help farmers protect their crops and improve their yields. Early detection prevents and cures disease in plants. Detecting diseases in plant leaves is essential for keeping crops healthy and productive. Traditional methods, such as having human experts visually inspect the leaves, can be slow, expensive, and inaccurate. The ability to identify plant leaf diseases may be drastically improved by deep learning, a highly effective approach. It offers the ability to automate the procedure, making it more efficient, precise, and widely available. Large datasets containing images sample of both healthy and infected plant leaves serve as the training material for deep learning models. Deep learning models that have been trained on a dataset of annotated plant leaf images can accurately identify whether new plant leaf images are healthy or unhealthy. Once trained, the models can correctly classify new photos of plant leaves as healthy or infected [19]. This works very well, even when the images of the leaves are difficult to interpret in inconsistent lighting conditions, backgrounds, and leaf positions. These systems can also be scaled up to be used in large farms [1]. Deep learning algorithms to identify plant leaf diseases are still in their early years, but they have the potential to be extremely useful to farmers. These methods can assist farmers in increasing crop yields, reducing crop losses, and saving time and money. Deep learning architectures have recently been developed by researchers implementing high-powered devices such as GPUs and servers. Due to the high cost of complex devices with GPUs, their use in agriculture is not possible. Deep learning models will become more accurate and scalable as they improve. This will increase their value to farmers and other agricultural professionals [9].

Here are some advantages of utilizing deep learning to detect plant leaf disease:

- High accuracy: Deep learning algorithms can accurately categorize plant leaves as healthy or unhealthy. This is especially crucial for early disease diagnosis, which can help to avoid large crop losses.

Figure 1: Various types of plant diseases [8]

- Scalability: Deep learning algorithms are capable of handling enormous datasets.
- Automated: These have the potential to automate the identification of plant leaf disease. This saves farmers time and money, and it may also assist to improve disease detection consistency.

2 Plant Disease Classification

Although there are multiple ways to categorize plant diseases, some of the most popular ones are as follows [10]

- By causal agent : Plant diseases are commonly categorized by their causal agents, which is the primary approach. This classification is based on what triggers the disease, leading to two fundamental categories of plant ailments: Infectious diseases: These diseases are instigated by living organisms like fungi, bacteria, viruses, and nematodes. Non-infectious diseases: In contrast, these conditions do not arise from living organisms but rather stem from environmental factors such as nutrient deficiencies, exposure to toxins, or physical injuries.
- By symptoms: This classification system is based on the visible symptoms of the disease. Some common symptoms of plant diseases include: Leaf spots : These are small, discolored areas on leaves. Blights : These are rapidly spreading diseases that cause leaves, stems, or flowers to wilt and die. Rusts : These are diseases that cause rust-colored pustules to form on leaves, stems, or flowers. Smuts : These are diseases that cause black or brown masses to form on leaves, stems, or flowers.

- By organ affected: This technique of classification is based on plant's effected area. Some common organs affected by plant diseases include : Roots: Root diseases can cause plants to wilt, stunt, or die. Stems: Stem diseases can cause plants to become weak and susceptible to breakage. Leaves: Leaf diseases can reduce the photosynthetic capacity of plants, leading to yield losses. Fruits: Fruit diseases can cause fruits to become discolored, shriveled, or rotten.

In addition to these common classification systems, plant diseases can also be classified by their mode of transmission, their geographic distribution, or their economic importance. The classification of plant diseases is an important tool for plant pathologists, as it allows them to identify and diagnose diseases, develop control strategies, and track the spread of diseases. The branch of science dedicated to the examination of plant diseases and its cause is called plant pathology [1]. It also involves identifying and managing plant diseases. Figure 1 shows various types of plant diseases from the Plant Village dataset.

3 Plant leaf disease detection process

It is the method of recognizing diseases in plants using images of their leaves. The procedure entails gathering photos, annotating them, preprocessing them, extracting features, and classifying them based on those derived characteristics. Figure 2 shows the general process of plant leaf disease detection.

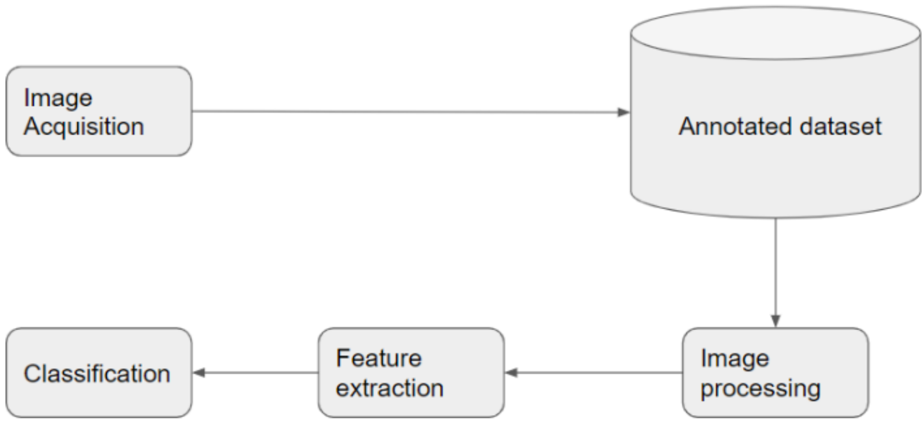

Figure 2: Plant Leaf Disease detection Process

3.1 Image Acquisition

This is the initial phase where images are gathered or obtained. It involves capturing or collecting images to be used for analysis.

3.2 Annotated Dataset

After acquiring the images, they are annotated.Annotation means adding relevant information or labels to the dataset. Annotated datasets are crucial for training machine learning models.

3.3 Image Preprocessing

In preprocessing we extract features having information and non-redundant data from the raw image to reduce the unnecessary resource wastage. This helps in decreasing model training time and increasing model inference speed.

3.4 Feature Extraction

Transforming raw data into useful set of features it is helpful for model to understand the pattern in data.

3.5 Classification

The process of classify a given set of data into classes. In image processing, it means assigning a label to a detected object based on extracted features.

4 Literature Survey

There are various studies that used different methods, including deep learning and classical machine learning, to classify, determine, and extract the features of plant diseases. It is compared in table 2 over different metrics and a figure 3 shown between model and architecture for better understanding. However, these studies exhibit several limitations. Many high-accuracy models require substantial computational resources, limiting their applicability in resource-constrained environments. Furthermore, models trained on controlled lab images often fail to perform well in diverse field conditions due to a lack of robust preprocessing and feature extraction techniques. The dependency on high-definition cameras and internet connectivity also restricts the widespread use of mobile applications in remote or under-resourced areas. Additionally, data imbalance and inadequate handling of complex backgrounds are significant issues that reduce the generalizability and reliability of these models.These methods have been widely used in agriculture to help farmers and other stakeholders detect and manage plant diseases more effectively. To summarize the literature survey shown table 1 contains advantages, disadvantages, and research findings.

Table 1: Compilation of Literature Survey

Ref.	Advantages	Disadvantages	Research Findings
[6]	Works well on complex background images	Low accuracy compared to other models due to a high number of parameters, leading to computational cost issues	Not suitable for low-end devices due to resource-intensive parameters
[19]	Good accuracy, but trained on lab images (may not generalize to complex backgrounds)	Selects only high covariant features, ignoring other relevant features; lacks image preprocessing or segmentation steps	Potential for improved accuracy with additional feature extraction steps
[3]	High accuracy on PlantVillage dataset, but requires many parameters	Training time and computational cost increase due to parameter count; performance may vary on complex backgrounds	Trade-off between accuracy and computational efficiency
[4]	Achieved high accuracy and precision with EfficientNet B5 and B4 models on PlantVillage dataset	High parameter count not suitable for low-end devices; biased data split for testing	Consider model complexity and data distribution for better generalization
[9]	High accuracy suitable for low-end devices	Trained on uniform background images; performance drop with complex backgrounds	Address complex backgrounds during testing for consistent performance
[2]	Requires fewer parameters, suitable for low-end devices	Achieves high accuracy on lab images but may not perform well on complex backgrounds	Balance between simplicity and performance
[14]	Introduces a new dataset for plant leaf detection	Low accuracy may benefit from a better model; consider image preprocessing	Enhance accuracy through preprocessing techniques
[16]	Mobile application with automatic background removal	Internet dependency for model operation	Suitable for low-end devices but requires an internet connection
[15]	Faster training, higher accuracy with MobileNet architecture	May not generalize well to datasets with different distributions	Efficient model for classifying bean images
[5]	Android application for online/offline use; handles multiple disease occurrences	Unequal image distribution affects classification performance	Address data imbalance during training
[7]	Accurate citrus leaf disease classification using SSCNN algorithm	Varying training/validation set ratio impacts accuracy; potential underfitting	Efficient Android app for citrus leaf detection
[11]	Enhanced potato leaf disease dataset	Limited to similar crops; adjust algorithm parameters for faster training	Expand crop diversity and optimize training time

In [6], the author used two CNN models,VGG19 and Inception Module, and named them INC-VGGN to detect rice and maize diseases. The model used pre-trained weights of ImageNet dataset. Two inception layers and a pooling layer were used by the researchers to replace the final layer of the VGG19 model. They added two new layers to the VGG19 model to help it gather high-dimensional features from the images and classify them more accurately. They also used data augmentation techniques to make the training dataset more balanced and to improve the performance of the model. A

92% average accuracy was attained when the model was tested using the Plant-Village dataset.

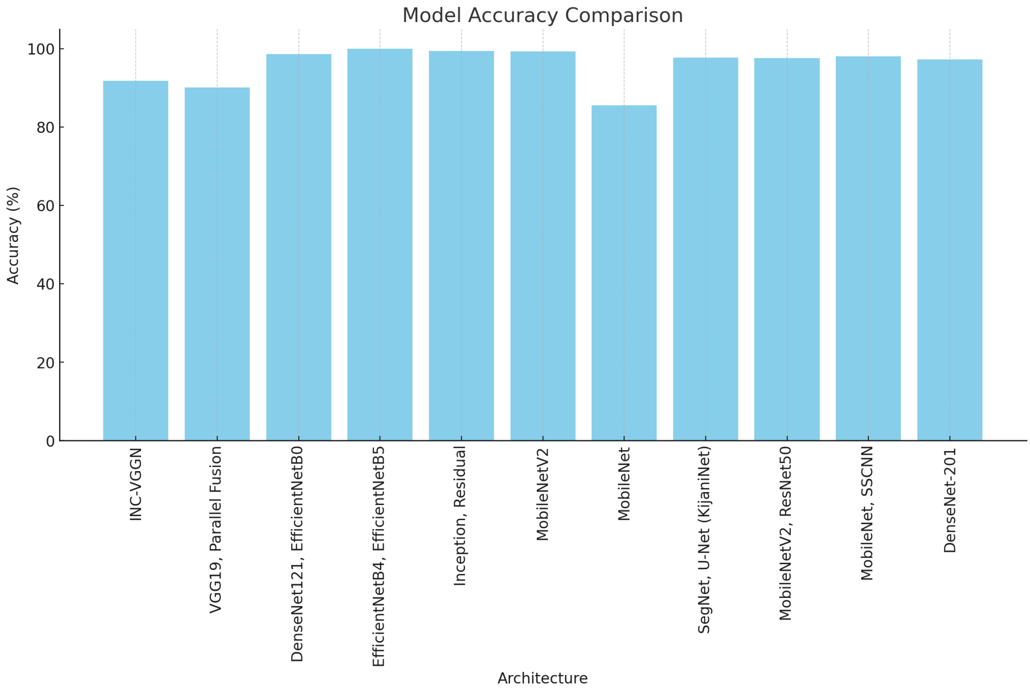

Figure 3: Accuracy Comparison of different Deep learning Model architecture

In [19], this researcher developed a method for crop recognition that involves extracting deep features from crops using a pre-trained VGG19 model, fusing the extracted features using a parallel fusion method based on PLS, and selecting the most discriminant characteristics by using a PLS projection approach. Crop identification is done lastly using the ensemble bagged tree classifier. This method achieved an average accuracy of about 90.1% in identifying plant diseases in the evaluated crops.

In [3], the author proposes a model based on deep learning that can distinguish between healthy and infected corn plant leaves using two pre-trained models, EfficientNetB0 and DenseNet121. Extracted features are combined using concatenation to create more enhanced feature set that helps model learn more effectively. With the help of data augmentation techniques, the model is trained on the Plant-Village corn subset dataset and has a 98.56% accuracy. This bar graph displays the number of classes each model was trained on. It helps to understand the complexity of the classification tasks each model handled.

In [4], the author used the EfficientNet to categorize plant leaf images from the PlantVil-

Table 2: Model Performance and Parameters for Plant Disease Detection

Ref.	Architecture	Datasets	Plants	Images	Classes	Metrics
[6]	INC-VGGN	PlantVillage, Created	Corn, Rice, Maize	4352	9	Acc. 91.83%
[19]	VGG19, Parallel Fusion	PlantVillage	Tomato, Corn, Potato	24164	17	Acc. 90.1%
[3]	DenseNet121, EfficientNetB0	PlantVillage	Corn	15408	4	Acc. 98.56%
[4]	EfficientNetB4, EfficientNetB5	PlantVillage	14 species	54305	38	Acc. 99.91% (Orig.), 99.97% (Aug.)
[9]	Inception, Residual	Rice, Cassava, PlantVillage	Rice, Cassava, Tomato	5932, 5956, 54305	5, 4, 17	Acc. 99.39%, 99.66%, 76.59%
[2]	MobileNetV2	PlantVillage	Tomato	18160	9	Acc. 99.30%
[14]	MobileNet	FieldPlant	Corn, Cassava, Tomato	5170	27	Acc. 85.55%
[16]	SegNet, U-Net (KijaniNet)	Created	Tomato	1408	5	mwIoU 0.9766, mbF1Score 0.9439
[15]	MobileNetV2, ResNet50	Created	Rice	2259	12	Acc. 97.56%
[5]	MobileNet, SSCNN	Created	Citrus leaf disease	2939	3	Train acc. 98%, Val. acc. 99%
[7]	MobileNet	Public bean dataset	Bean	1296	3	Train acc. 97%, Val. acc. 92.97%
[11]	DenseNet-201	Created (PlantVillage)	Potato	3852	5	Acc. 97.2%

lage dataset. The The EfficientNet architecture's B5 and B4 models surpassed all other deep learning models on both the original and augmented test datasets. Both models obtained very high accuracy and precision on the plant disease detection task, with the B4 model slightly outperforming the B5 model. The results show that the EfficientNet architecture is excellent for classifying plant leaf diseases and that it outperforms other deep learning models when using transfer learning with pretrained models from ImageNet. In figure 4 bar graph displays the number of classes each model was trained on. This model shows the highest classes. It helps to understand the complexity of the classification tasks each model handled.

The authors of [9] propose a model for plant disease monitoring that is designed to be efficient and effective on low-end devices. The model incorporates inception layers and residual connections to enhance accuracy while employing depthwise separable convolution, a technique that effectively reduces the parameter count. This makes the model more efficient and less computationally expensive. The model was trained and tested on 3 different plant disease datasets, including the rice disease, PlantVillage, and cassava leaf disease dataset and achieved accuracies of over 99% on two of the datasets and over 76% on the third dataset.

This study [2] proposes a new method for identifying diseases in tomato leaves using transfer-learning and a lightweight model. The method uses a pre-trained MobileNetV2 architecture and a classifier network to extract features from tomato leaf images. It also uses a technique called CLAHE to improve the visibility of disease spots in images with poor lighting. The method uses runtime augmentation to address dataset imbalance, overfitting, and data leaking issues. When evaluated on the Plant Village dataset, it achieved an accuracy of 99.30%. The system is lightweight and fast with size of 9.60MB, while maintaining comparable accuracy. The system was also more robust to poor lighting conditions and dataset imbalances. This [14] study proposes a new dataset called

Figure 4: Bar graph for the number of classes each model trained

FieldPlant. The dataset was collected from plantations in Cameroon and contains 5,170 images of 27 different plant diseases. The researchers trained machine learning models on three different datasets of plant disease images: FieldPlant [18], PlantVillage [8], and PlantDoc [17]. Particularly for images with real world surroundings and multiple leaves, they discovered that the models trained on FieldPlant outperformed the models trained on the other two datasets. This dataset is more challenging than existing datasets, which makes it a better testbed for evaluating the performance of new models. The dataset also includes images of diseases that are not present in other datasets, making it more useful for farmers in developing countries. The author in [16] proposes a new deep learning approach to automatically removing the background from leaf images captured in mobile apps. This approach is based on fully convolutional neural networks (FCNNs) and exceed other baseline approaches in comparison of speed, accuracy and automation. The FCNNs used in this approach are SegNet and KijaniNet, and the dataset used to train the FCNNs was collected from three smallholder farms in Kenya and the internet. This method has the possibility to be used in a variety of mobile applications for identifying and diagnosing plant leaf diseases.

For beans leaf disease classification [15] the author used a novel deep learning approach that uses MobileNet model. Remarkably, this method achieves outstanding classification performance, featuring training accuracy as 97% and testing accuracy as 92%. In comparison to other existing methods, the proposed approach excels in accurately identifying plant leaf diseases. The best experimental results were obtained by employing the adam-optimizer, setting a learning rate of 0.001, and utilizing a batch size of 32. The study shows the importance of architectural selections, including the use of MobileNetV2 under controlled settings, to improve performance and facilitate learning.

In [5] the author proposed identification of rice diseases and nutrient deficiencies using smartphone image processing and transfer learning techniques. Different image segmentation techniques, such as foreground extraction, were employed to identify affected portions of the plants. The study optimized models and procedures for offline use on smartphones and developed a dynamic framework which is helpful to improve classification performance of new images. For cloud based architecture ResNet50 model and for offline mode MobileNetV2 outperforms others.

In [7], the author compares two different CNN architectures, MobileNet and Self-Structured (SSCNN), for identifying citrus leaf diseases. The SSCNN model outperformed MobileNet in terms of accuracy and computation time, making it a more cost-effective tool for detecting citrus disease. The SSCNN design was proven to be more acceptable and provide higher overall performance than the MobileNet CNN architecture. It is used to categorize more than three types of citrus leaf diseases. The models were trained and validated using citrus image datasets, with different training and validation sets for each architecture. The learning process and performance varied between the two techniques.

Existing techniques for potato leaf disease classification only classify into two classes in 'Plant Village Dataset'. In study [11] introduced a novel technique based on an improved deep learning algorithm that classifies potato leaves into five classes. The suggested technique accurately classifies potato leaf diseases by combining an efficient DenseNet model with an additional transition layer. To deal with unbalanced data it uses a reweighted cross-entropy loss function and to minimize over-fitting it uses dense connections with regularization power. On the testing set, the suggested method overperformed existing techniques in detecting and classifying potato leaf diseases, achieving 97.2% accuracy.

5 Challenges and Future Scope

Based on the study performed by reading various research papers, the following points have been identified that have a immense impact on the results:

5.1 Diversity of plant diseases:

Plant disease are very diverse, and each type of disease has its own unique symptoms. Different plants can exhibit different symptoms of disease, and a disease's appearance can vary depending on the environment.

5.2 Dataset availability:

There are not many large, high-quality, annotated datasets of plant leaf images freely available. The majority of studies have utilized the PlantVillage dataset, which contains images of corn, tomato, potato, etc., that were captured in a laboratory with a similar background. But when these systems are tested in actual environments, their performance drastically declines. Complex backgrounds are a significant factor in this performance decline, and studies have shown that removing the background can increase the accuracy of disease detection [14]. Comparison of different dataset are shown in table 3.

Table 3: Overview of publicly available dataset on plant leaf disease Images

Ref.	Name of DataSet	Number of Images	Findings	Number of Plant disease
[8]	PlantVillage	61486	Images were captured in a laboratory with a uniform background which causes when models trained with this dataset are tested in actual environments, their performance drastically declines.	14 crop with 39 different Plant disease
[17]	PlantDoc	2598	Some images are downloaded from the internet. Presence of misclassification, Limited number of images.	13 plant species with 30 classes of diseases and healthy
[18]	FieldPlant	5170	Collected Outdoor images with complex background	27 different plant diseases classes

5.3 Complexity of leaf images:

Leaf images can be complex and noisy, making it difficult to extract the features that are important for disease detection.

5.4 Model complexity and interpretability :

Deep learning models are powerful tools, but they can be difficult to use. They can be slow to train and require a lot of computing power, which makes them hard to use on devices like smartphones. Additionally, it can be hard to understand why a deep learning model made a particular prediction.

5.5 Real-time detection:

Real-time plant leaf disease identification models are required. This requires the development of efficient and scalable algorithms that can be run on mobile devices or embedded systems.

Plant leaf disease detection is a promising technology with the potential to revolutionize agriculture. By detecting diseases early, farmers can prevent them from spreading and causing major crop losses. Plant leaf disease detection can also help farmers to make informed decisions about resource allocation and targeted interventions, leading to healthier plants and more sustainable agricultural systems. As machine learning techniques continue to improve and more data becomes available models become more robust, more accurate and efficient in the years to come.

6 Conclusion

In order to identify plant diseases from leaf images, various deep learning models have been reviewed and summarized in this paper. In comparison to earlier machine learning techniques, deep learning methods have been shown to produce better outcomes. Transfer learning and data augmentation are some techniques that can be used to make deep learning models more accurate and efficient. Deep learning can be used to create automated tools for the rapid and precise diagnosis of plant diseases. Plant diseases come in a wide variety of forms, so it is challenging to create a single model that can recognize them all. There is a problem for the publicly availability of annotated datasets and another common problem in detection is data imbalance and overfitting. There are some ways to address these problems, such as data augmentation and image processing. Many recent studies have used deep learning architectures to diagnose plant leaf diseases. The performance of certain models under specific conditions can be attributed to their design and the nature of the training data. For instance, models like EfficientNet B5 and B4 perform well in controlled environments with consistent lighting and simple backgrounds because they are designed to leverage deep layers and extensive parameters for high accuracy. However, these models are computationally intensive, making them impractical for real-time applications or use on low-end devices. On the other hand, MobileNet, designed with fewer parameters and optimized for mobile devices, offers a good balance between accuracy and computational efficiency, but its performance may degrade with complex and diverse datasets. Future work in this could focus on using deep learning models compatible with low-end devices for real-world implementation in the field. These systems could also provide information about the stage of the disease, the percentage of plant damage, and treatment suggestions.

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