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Research paper

CNN-Based Plant Disease Detection from Leaf Images

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Abstract

Crop diseases pose a significant threat to global food security, and accurately identifying these diseases remains a challenging task. Various diseases—such as gray leaf spot, common rust, northern leaf blight, and others—affect different parts of the plant, including leaves, stems, and roots, ultimately leading to substantial yield losses. Given the wide range of disease types and their visual similarities, manual classification by human experts is both time-consuming and prone to high error rates. To address these challenges, there is a growing need for automated systems capable of detecting and classifying plant leaf diseases with high accuracy. This technical review paper presents a comprehensive overview of common plant diseases, their classifications, and the techniques employed to manage them. Additionally, it explores existing literature and recent advancements in deep learning-based approaches, particularly those using publicly available benchmark datasets for automated plant leaf disease detection and classification.

Keywords: *CNN; Classification; Disease Detection; Leaf Images; Prediction.*

1. Introduction

In today's world, agriculture is an essential component in the process of producing food to satisfy the needs of a growing population. The combined value of agriculture, fishery, and forestry is around 18% of the GDP. Despite this fact, the contribution of agricultural goods to the gross domestic product of India is steadily decreasing from one year to the next [1]. Infectious diseases of plants are the primary contributor to this disastrous drop in agricultural production. The conventional approaches for determining the severity of a disease involve making a visual assessment of the infectious signs and determining the characteristics of the disease symptoms [2].

In order to accurately observe and assess the severity of an illness, a trained individual is necessary, and the only way to acquire such abilities is via extensive inquiry and research. This approach, developed by Kaur et al [3], takes significantly more time and substantially raises the bar for the level of expertise required to diagnose plant diseases. Still, there is a demand for novel approaches to cope with future trends in agriculture and overcome problems in increasing productivity. Therefore, improvements to already-existing techniques aswell as the invention of new techniques are required for the implementation of an effective automatic plant disease detection system that is superior to the visual evaluation process, Ferentinos. These improvements and inventions are required for the Ferentinos plant disease detection system [4].

During all stages of a plant's life cycle, including development and growth, it is subject to influence from environmental factors such as temperature, rainfall, climatic shifts, and sunlight. The pH of the soil, the availability of nutrients, and the amount of moisture in the soil are all essential for the proper development of plants [5]. Because plant diseases are present, there is a possibility that both the quantity and the quality of the eventual output may be severely diminished. According to Barbedo et al. [6], estimates provided by the Food and Agriculture Organization (FAO), diseases and pests are responsible for approximately 25% ofall crop losses. Therefore, it is a significant parameter that needs to be under control. If this doesn't happen, it might hurt the growth of plants, which wouldultimately damage agricultural output.

The remainder of the paper is structured as follows: Section 2 is a review of the different typesof plant leaf disease done over the years. Section 3 discusses the different publicly availed datasets and describes information about the datasets. Section 4 is focused on current researchrelated to different types of techniques for identifying plant leaf disease, and Section 5 is focused on conclusions and the future scope of this research.

2. Literature Survey

A lot of classification methods have been proposed to deal with the plant leaf diseaserecognition system. Machine learning models for the prediction of these plant leaf diseases were found to differ in accuracy. Various techniques are at present being used for therecognition of plant leaf diseases by the application of computer vision. The traditional classification is based on either supervised or unsupervised learning methods. Some researchershave proposed plant leaf disease classification using supervised learning methods such as support vector machine, artificial neural networks, random forest, k-nearest neighbours,decision tree, and sparse representation classifier [7]. The support vector machine is a supervised non-parametric learning technique; therefore, no assumption is made on data distribution. Zhang et al. [8] have used the genetic algorithm to support vector machines
(SVMs) for the classification of Tomato leaf diseases. To recognize and classify tomato leaf diseases and healthy leaves. Alehegn [9] developed a technique based on color, texture, and morphological features for the classification of plant disease-affected leaves and healthy leaves.
A study in comparison of support vector machine (SVM) and ANN was performed by Ren etal. [10]. Algorithms for colour extraction and texture features were developed, which were thus used to train SVM and ANN classifiers. The study presented a reduced-feature-set-based approach for the recognition and classification of images of plant diseases. The results revealed that the SVM classifier was progressively reasonable for the identification and classification of plant diseases. An SVM classifier was 92.17% than the ANN classifier, which had an accuracy of 87.4%. Computational Efficiency: SVMs are known for their efficiency in high-dimensional spaces, especially when the number of dimensions exceeds the number of samples. They are effective in scenarios where the data is not linearly separable by employing kernel tricks. However, SVMs can become computationally intensive as the size of the dataset increases, particularly during the training phase, which involves solving a quadratic optimization problem.
Robustness: SVMs are generally robust to overfitting, especially in high-dimensional spaces, due to their structural risk minimization principle. They perform well in scenarios with a clear margin of separation and are less prone to overfitting compared to ANNs when the dataset is small or medium-sized.
Sankaran et al [11] presented a review of the most distinguished conventional methods of plant disease detection techniques. These techniques include spectroscopic-based, imaging-based, and volatile profiling-based plant disease detection methods. The paper compares the benefits and restrictions of these approaches. In recent years, CNN has been used in various agricultural applications such as disease leaf object classification, leaf disease prediction, and disease detection. However, in the literature, plant leaf disease identification using deep learning has not been handled much. Therefore, novel approaches in this area are required. The authors in [12], [13] presented deep CNNs for solving disease identification tasksusing different datasets and different numbers of layers for various plant leaf diseases.

3. Plant Leaf Diseases and Types

The leaves of a plant are the most essential parts of the plant. Deterioration and damage to leaves can be attributed to a number of causes, including inadequate nutrition, illnesses, pests,a lack of sunshine, and floods [14]. One of the key limiting factors in plant development is leaf loss from disease. When a plant is infected, its ability to perform several tasks (including respiration, photosynthesis, germination, pollination, and many others) is greatly diminished. In order to increase crop productivity, it is thought that early identification of leaf disease is a crucial task [15]. Common disease-causing microorganisms include fungi, viruses, and bacteria. It is because of these infections those agricultural yields have decreased. Fungal infections, in particular, have been shown to have a significant impact on crop development [16]. Early blight, Late blight, Leaf spot, Bacterial spot, Common rust, Apple scab, Downy mildew, Anthracnose, etc., are all names for foliar diseases that can affect plants as shown in Figure 1.

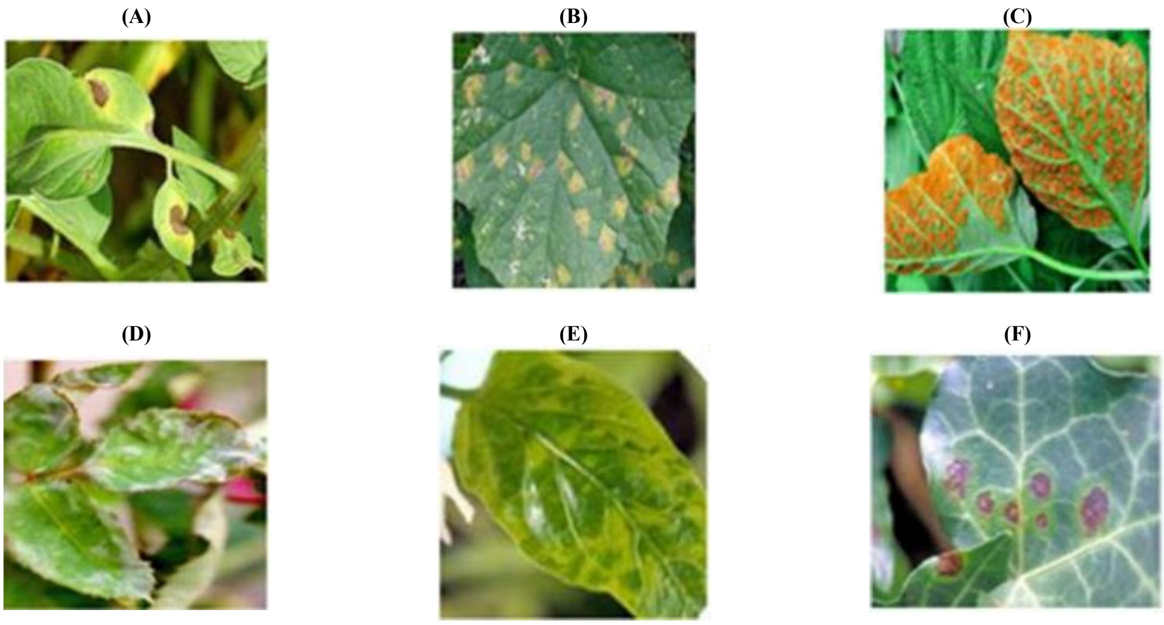

Fig. 1: Plant Leaf Disease Types (A) Early Blight, (B) Downy Mildew, (C) Common Rust,(D) Powdery Mildew, (E) Mosaic Virus, (F) Leaf Spot

4. Dataset Collections

A dataset plays an important role in identifying and classifying plant leaf disease. There are so many publicly available benchmark datasets available for the classification and identification of plant leaf diseases.

4.1. Plant Village Dataset

The plant leaf disease image collection in its original form was obtained from the repository of open data for the Plant Village [17]. The Plant Village dataset includes a total of 54,309 images in its entirety. The images are organised into 38 distinct diseases that may be seen on 14 different types of crops. The majority of the images were taken within a laboratory under strictly regulated circumstances and with consistent settings for the backgrounds. Tomatoes, blueberries, cherries, maize, grapes, oranges, peaches, peppers, potatoes, raspberries, soybeans, squash, strawberries, and strawberries are all part of the plant species. Every plant in the dataset has both the "healthy leaf" and "most common disease leaf" classifications. Every image in the data set has a 256×256 pixel resolution. Each category may contain anywhere from 152 images to 5,507 images. Figure 2 shows a random selection of images taken from the complete dataset.

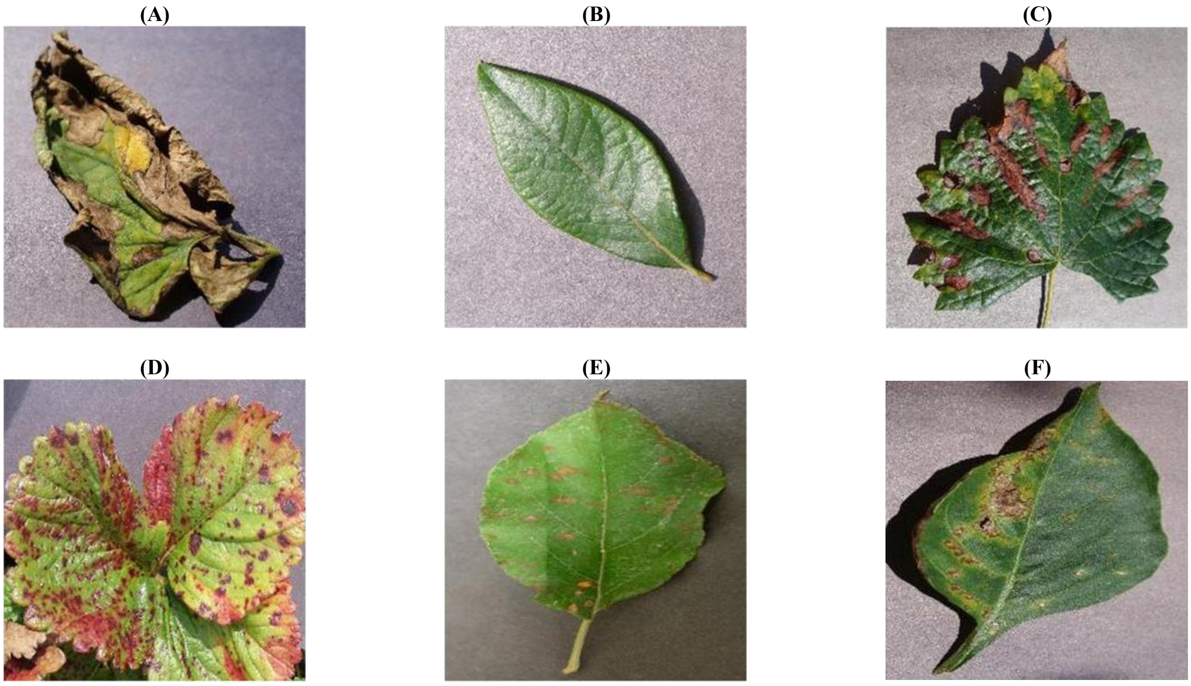

Fig. 2: Sample Disease-Affected Images from Plant Village Dataset.

4.2. Digipathos Dataset

The Digipathos dataset should consist of 46,513 images across 171 diseases affecting 24 different crops [18]. As shown in Figure 3, out of 46513 images, 2326 images are capturedunder the controlled lab conditions with uniform backgrounds. The remaining 44,187 images consist of cropped disease lesions. Every image in the data set has a 128×128 pixel resolution.

Fig. 3: Sample Disease-Affected Images from the Digipathos Dataset.

4.3. NLB Dataset

Using UAS-based airborne photography, handheld imagery, and positioning a camera on a boom, a dataset was collected that included 18,222 field images of Northern Leaf Blight (NLB) infected maize [19]. NLB is a prevalent leaf disease that affects corn. As can be seen in Figure 4, the NLB dataset is made up of real-field images that have been annotated with 105,735 diseases. This dataset only contains corn leaf images that have a single disease, thus it cannot be used to diagnose many diseases at the same time. Every image in the data set has a 224×224 pixel resolution.

Fig. 4: Sample Corn Disease Affected Images from the NLB Dataset.

4.4. Cassava Disease Dataset

Similarly, the Cassava disease dataset is one of the publicly availed benchmark datasets that was acquired under field conditions [20]. The dataset consists of 5655 images for five distinct disease classes: healthy, cassava bacterial blight, cassava brown streak disease, cassava greenmite, and cassava mosaic disease. The dataset was collected in the field and featured intricate backgrounds, as illustrated in Figure 5. As a result, this dataset may be used to train models that can recognise cassava diseases in field settings. Every image in the data set has a 128×128 pixel resolution.

Fig. 5: Sample Images from Cassava Dataset.

Table 2 shows information about the different types of plant leaf disease benchmark datasets. The tables describe the classes, images in each class, image size, and total images. From the table, we can observe that the PlantVillage dataset is one of the largest datasets, and also, the dataset can sufficiently handle the different types of diseases for the different types of plant leaves. The remaining datasets consist of limited leaf disease for the limited crops.

Table 2: Different Benchmark Datasets for Plant Leaf Disease

S. No.	Dataset Name	Classes	Images in Each Class	Image Size	Total Images
1.	Plant Village	38	152 – 5507	256×256	54,309
2.	Digipathos	24	1938	128×128	46,513
3.	NLB dataset	6	3037	224×224	18,222
4.	Cassava Disease Dataset	5	1131	128×128	5655

5. Plant Leaf Disease Identification Techniques

This section provides a comprehensive analysis of the methods used for automated disease prediction, including a comparison of pre-processing stages, feature extraction, and classification stages. As shown in Figure 6, we can classify those techniques into twocategories, namely machine learning techniques and deep learning techniques.

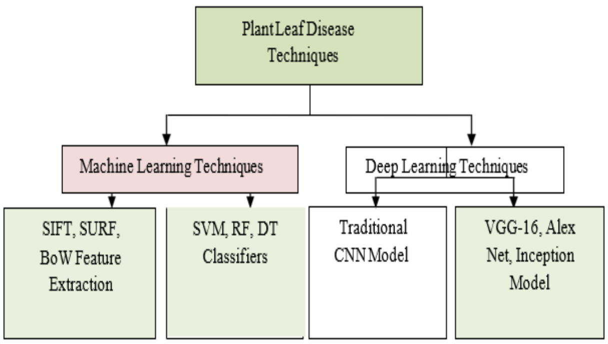

Fig. 6: Plant Leaf Disease Classification Techniques.

5.1. Machine Learning Techniques

Machine learning is one of the emerging techniques for classifying plant leaf disease in the Plant Village dataset. The sequence of steps in machine learning based plant leaf disease classification is shown in Figure 7. There are three steps to be followed in a machine learning based plant leaf disease classification system [21].

- Pre- Pre-Pre-Processing Phase
- Feature Extraction and
- Classification

5.2. Pre- Processing Stage

Image quality is improved during the pre-processing stage by the reduction of distortion, which makes subsequent processing more straightforward. The processes of smoothing, enhancing, cropping, and colour space conversion are among the most common pre-processing techniques [22]. The functionality of this module shifts in different ways depending on the image quality. The filters are applied to the image to achieve the desired enhancements, such as improved contrast and brightness. Also, the image is sharpened with a Laplacian filter. In addition, histogram equalisation and Gabor wavelets are employed to filter and regulate the effects of different illumination sources [23].

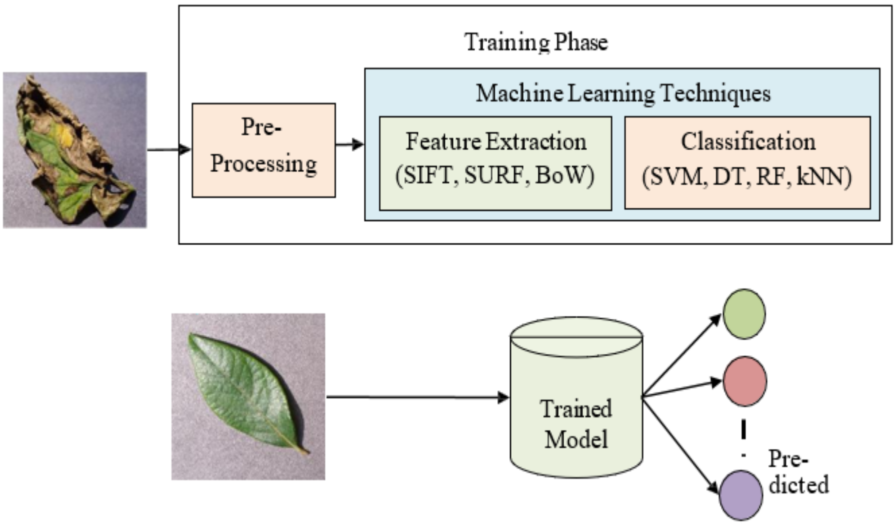

Fig. 7: Sequence of Machine Learning Based Plant Leaf Disease Recognition System.

5.3. Feature Extraction Stage

The second and important step is feature extraction, which is used to extract the features fromthe input images. The features may consist of low-level and high-level features [24]. The low-level feature is to extract the boundary of objects or edges of objects. Similarly, the high-level feature extracts the internal shape of objects. There are several distinct methods for the extraction of features, the most common of which are the Histogram of Oriented Gradients (HoG) feature, Bag-of-Words (BoW) feature, Scale Invariant Feature Transform (SIFT) features, Speed-Up Robust Feature (SURF) features, and the Haar-like features [25,26].

5.4. Classification Sage

Classification is a method that is employed in the process of determining the category or classthat the new data falls within. Two distinct categories can be applied to the categorization approach; these are supervised learning and unsupervised learning [27]. Training a classifier with an existing dataset that has been labelled is the sum and substanceof the supervised classification approach. A few examples of supervised learning techniques are the Support Vector Machine (SVM), Artificial Neural Network (ANN), k-Nearest Neighbor (kNN), Logistic Regression, Decision Tree, and Random Forest. For example, Abu Sarwar Zamani et al. [28] developed a machine learning technique based on color, texture, and morphological features for the classification of plant disease-affected leaves and healthy leaves. The above-mentioned machine learning techniques are not saturated for handling the huge amount of plant leaf disease datasets. In order to handle these issues, we have to take the convolutional neural network and the deep CNN model as recent and emerging models.

5.5. Deep Learning Techniques

Deep learning is a machine learning technique that is used to build a model that learns from data such as images, videos, audio, and text and performs tasks such as classification and detection. Scene classification is used to classify scenes using various scene classification models, such as Convolutional Neural Network (CNN) [29] and Deep CNN models [30]. Deep learning-based approaches include CNN, transfer learning (VGG-16 and VGG-19) [31,32], Recurrent Neural Network (RNN), Auto Encoder, and Generative Adversarial Network. For image classification, CNN and transfer learning models are commonly used. CNNs are extensively used for image segmentation and classification.

Despite the fact that CNNs were first created in 1989, their outstanding success in the ImageNet Competition in 2012 garnered them even more attention. The computational complexity of CNN design is increasing as the number of layers, neurons with millions of weights, and connections between different neurons increases. The basic block diagram of CNN is shown in Figure 8, which includes convolutional, pooling, activation function, and fully linked layers, each of which serves a different purpose.

5.6. Fully Connected Layer

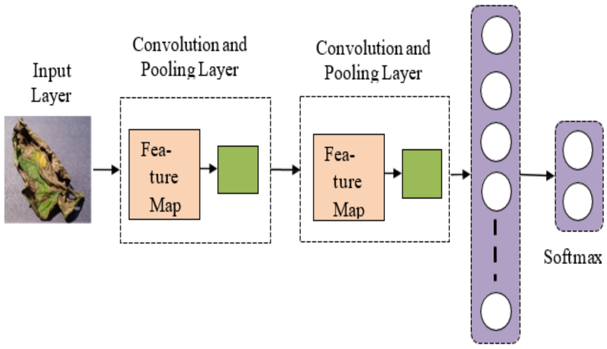

Fig. 8: Working flow of Convolutional Neural Network for Disease Recognition System.

By convolving input images across the kernel, the convolutional layer generates feature maps. As the value is transferred to the next layer, the results from the preceding convolutional layers are downsampled using the maximum or average of the defined neighborhood in the pooling layer. The loss function is coupled with the remaining layers of the CNN model output to give a forecast of the input data. Finally, network parameters are determined by minimizing the loss function between prediction and ground truth labels while maintaining regularization requirements. In addition, backpropagation is used to change the network weights at each iteration until convergence. For example, R. Sangeetha and M. MaryShanthi developed a deep learning technique based on a CNN model for the classification of plant disease-affected leaves and healthy leaves [33]. Similarly, Deepalakshmi et al. [34] proposed an automated system to identify the diseased and healthy leaves of distinct plants by extracting features from input images using a CNN algorithm.

6. Conclusion

In this technical review study, we examined various approaches that utilize image processing techniques for detecting plant leaf diseases. The field of automated disease identification and classification using computer vision has seen significant advancements in recent years. However, there is still room for improvement, and no single method has proven to be universally effective for detecting all types of plant leaf diseases. Moreover, deep learning methods demonstrate superior accuracy and robustness compared to traditional ML models, especially in complex real-world scenarios involving noisy or imbalanced datasets. Recent advancements, such as the integration of vision transformers and hybrid models combining CNNs with attention mechanisms, have further enhanced the ability to capture long-range dependencies and contextual information in plant images, pushing the boundaries of disease classification performance. As a result, deep learning approaches have become increasingly popular in modern plant disease detection systems, not only for their accuracy but also for their ability to integrate with mobile and edge computing platforms. This facilitates real-time, scalable, and cost-effective disease monitoring solutions that can significantly aid farmers and agricultural experts in making timely decisions, ultimately improving crop health and yield.

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