

# Diverse Plant Leaf Disease Detection Using CNN

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**Abstract:** Recent advances in computer vision have led to the development of a robust learning technique that can identify and diagnose plant diseases using photos captured by a camera. This practical approach can help detect various illnesses in different plant species, including apples, corn, grapes, potatoes, tomatoes, and sugar cane. The system's architecture specifically targeted these plants for detection and recognition, and it can detect several plant diseases. To develop deep learning models for plant disease detection and recognition, scientists used 35,000 photos of both disease-free and diseased plant leaves. The system achieved up to 100% accuracy in identifying the type of plant and the diseases affecting it, with the trained model achieving an accuracy rate of 96.5%. The technique involved using convolutional neural networks, computer vision, deep learning, and plant disease recognition.

**Keywords:** plant disease recognition, deep learning, computer vision, convolutional neural network.

## I. INTRODUCTION

The objective of this study is to propose a deep convolutional neural network model that can effectively and accurately detect various plant leaf diseases using their images. Detecting plant diseases can be challenging, especially for novice farmers who lack the knowledge of professional plant pathologists. An automated system that can recognize crop diseases based on visual symptoms can greatly benefit farmers as a verification tool in disease detection. In the past, several techniques have been employed, including digital image processing and neural networks, to achieve fast and precise detection of leaf diseases. This study aims to leverage these techniques to develop an automated plant leaf disease detection system.

The proposed method for diverse plant leaf disease detection utilizes Convolutional Neural Networks (CNNs), which utilizes computer vision to automatically identify and classify plant leaf diseases. The technique involves training a deep learning model on a dataset of labeled images of healthy and diseased plant leaves. By extracting features from the images, the CNN model can categorize them into different groups based on learned patterns. The accuracy of the CNN model depends on the quality and size of the dataset, as well as the CNN's architecture and parameters. Plant leaf diseases can have a significant impact on crop yield and quality. Early detection and treatment are essential to reduce losses. However, traditional methods of identifying plant diseases through visual inspection by experts can be time-consuming and expensive.

CNNs have emerged as a promising technology for detecting plant diseases due to their ability to provide a faster and more cost-effective solution. With accurate identification of plant diseases, this technology has the potential to improve crop yields and revolutionize the agriculture industry. By enabling farmers to detect and treat diseased plants, CNNs can lead to more efficient and sustainable farming practices quickly and easily.

## II. LITERATURE SURVEY

### 1. TITLE : Plant Disease Detection and Classification by Deep Learning.

**AUTHOR: Muhammad Hammad Saleem 1 , Johan Potgieter 2 and Khalid Mahmood Arif 1.**

The timely identification of plant diseases is crucial as they can significantly affect the growth of plants. While Machine Learning (ML) models have been employed for detecting and classifying plant diseases, the advancements in Deep Learning (DL) have shown potential for increased accuracy. Various DL architectures have been developed or modified and accompanied by visualization techniques to detect and classify plant disease symptoms. Additionally, different performance metrics are utilized to evaluate these techniques and architectures. This review

aims to comprehensively explain the DL models used to visualize plant diseases while identifying research gaps for greater transparency in detecting diseases in plants before their symptoms become apparent.

**Keywords: plant disease; deep learning; convolutional neural networks (CNN).**

## **2. TITLE: Real-Time Detection of Apple Leaf Diseases Using Deep Learning Approach Based on Improved Convolutional Neural Networks.**

**AUTHOR: PENG JIANG<sup>1</sup>, YUEHAN CHEN<sup>1</sup>, BIN LIU<sup>1,2,3</sup>, DONGJIAN HE<sup>2,3,4</sup>, AND CHUNQUAN LIANG.**

This article proposes a novel approach for the real-time detection of five common apple leaf diseases using an improved convolutional neural network (CNN) model. The current research lacks a fast and accurate detector for apple diseases, which is necessary for the healthy development of the apple industry. The authors constructed an apple leaf disease dataset (ALDD) comprising laboratory images and images captured under real field conditions, utilizing data augmentation and image annotation technologies. The proposed INAR-SSD (SSD with Inception module and Rainbow concatenation) model utilizes GoogleNet Inception structure and Rainbow concatenation to detect five common apple leaf diseases. The model was trained on a dataset of 26,377 images of diseased apple leaves and achieved a detection performance of 78.80% map on ALDD, with a detection speed of 23.13 FPS. The INAR-SSD model provides a high-performance solution for the early diagnosis of apple leaf diseases that can perform real-time detection with higher accuracy and faster detection speed than previous methods.

**Keywords: Apple leaf diseases, real-time detection, deep learning, convolutional neural networks, feature fusion.**

## **3. TITLE: LEAF DISEASE DETECTION AND FERTILIZER SUGGESTION.**

**AUTHOR: Indumathi.R, Saagari.N, Thejuswini.V, Swarnareka.R.**

The agricultural industry is facing numerous challenges, including the prevalence of diseases that affect plant leaves. To address this issue, a system has been developed that can detect the affected area of a leaf and identify the disease that has caused the damage. The proposed system relies on Image Processing techniques, which are commonly used to predict diseases in plant leaves. To improve accuracy, the system employs K-Medoid clustering and the Random Forest algorithm. After pre-processing the image, the clustering method is applied to determine the affected region of the leaf. Then, 13 parameters such as Mean, SD, Entropy, RMS, Variance, Smoothness, Kurtosis, Skewness, IDM, Contrast, Correlation, Energy, and Homogeneity are extracted and used to measure the accuracy and identify the disease. By utilizing these techniques, the proposed system offers a more effective solution for detecting and identifying plant leaf diseases.

**Keywords: Image Processing, Clustering, Classification, Detection of Leaf Disease, Accuracy, Pre-processed.**

## **4. TITLE: Plant Pathology Disease Detection in Apple Leaves Using Deep Convolutional Neural Networks. Apple Leaves Disease Detection using EfficientNet and DenseNet.**

**AUTHOR: V V Srinidhi<sup>1</sup>, Apoorva Sahay<sup>2</sup>, K. Deeba<sup>3</sup>.**

Plant diseases have caused significant annual yield losses of approximately 14% globally, leading to suffering for millions of people worldwide. Plant pathology is the scientific study of plant diseases that aims to improve plant survival rates under unfavourable environmental conditions and parasitic microorganisms that cause disease. Environmental factors such as temperature, pH, humidity, and moisture contribute to the development of plant diseases. Misdiagnosis of plant diseases can lead to the misuse of chemicals, resulting in economic loss, environmental imbalances, pollution, and the emergence of resistant pathogen strains. The current disease diagnosis process is time-consuming, expensive, and relies on human scouting. The use of automatic disease segmentation and diagnosis from plant leaf images can be a viable alternative to the current process. The automatic plant disease detection process involves image acquisition, pre-processing, and segmentation, followed by augmentation, feature extraction, and classification using models. This project proposes the use of Deep Convolutional Neural Networks, namely EfficientNet and DenseNet, to detect Apple plant diseases from images of apple plant leaves and accurately classify them into 4 categories, including "healthy," "scab," "rust," and "multiple diseases." The apple leaf disease dataset is improved using data augmentation and image annotation techniques, such as Canny Edge Detection, Blurring, and Flipping. The proposed models using EfficientNetB7 and DenseNet provide accuracies of 99.8% and 99.75%, respectively, and overcome known shortcomings of convolutional neural networks.

**Keywords: Machine Learning, Deep Convolutional Neural Networks, Data Augmentation, Canny Edge Detection, EfficientNet, DenseNet, Model Scaling, Feature Reuse.**

## **5. TITLE: Plant Disease Detection Using Machine Learning Techniques.**

**AUTHOR: Divyanshu Varshney, Burhanuddin Babukhanwala, Javed Khan, Javed Khan, Dr. Ashutosh kumarsingh.**

Agriculture is a crucial component of the Indian economy, providing livelihoods to many people. Plant diseases can significantly impact plant production, but early and accurate detection can lead to improved health and economic growth. However, traditional approaches to disease detection are time-consuming and labor-intensive. Machine learning techniques can be used to identify diseases caused by bacteria, viruses, and fungi. This study discusses various machine learning algorithms used for disease identification, including image acquisition, feature extraction, categorization, and result display. The paper aims to conduct a thorough analysis of techniques for identifying plant diseases using image analysis and suggests the appropriate fertilizers to be used once the disease is detected. Additionally, the study describes the pests and insects responsible for the outbreak of disease.

**Keywords: Disease Detection, Features Extraction, Machine Learning, Deep Learning, SVM.**

### III. METHODOLOGY

**Proposed system:** We propose an end-to-end trainable system for plant leaf disease detection. In contrast to the existing deep neural network-based methods which directly estimate the latent clean image, the network use filter to remove noise. First, the leaf samples were collected, and images were acquired. The leaf images were then pre-processed and fed into the feature extraction step. Lastly, the extracted features were trained and classified by using convolutional neural network algorithm. And finally, it detects plant leaf disease.

#### **Software:**

Image processing software: Image processing software can be used to analyse the images captured by the camera and detect any signs of disease in the plants.

Machine learning algorithms: Machine learning algorithms such as deep learning can be used to train the system to detect specific diseases in plants.

#### **Benefits:**

Real-time monitoring: The system allows for real-time monitoring of plant diseases, which can help farmers take timely action to prevent the spread of disease.

Early detection: Early detection of plant diseases can help prevent significant crop losses, resulting in higher yields and profits for farmers.

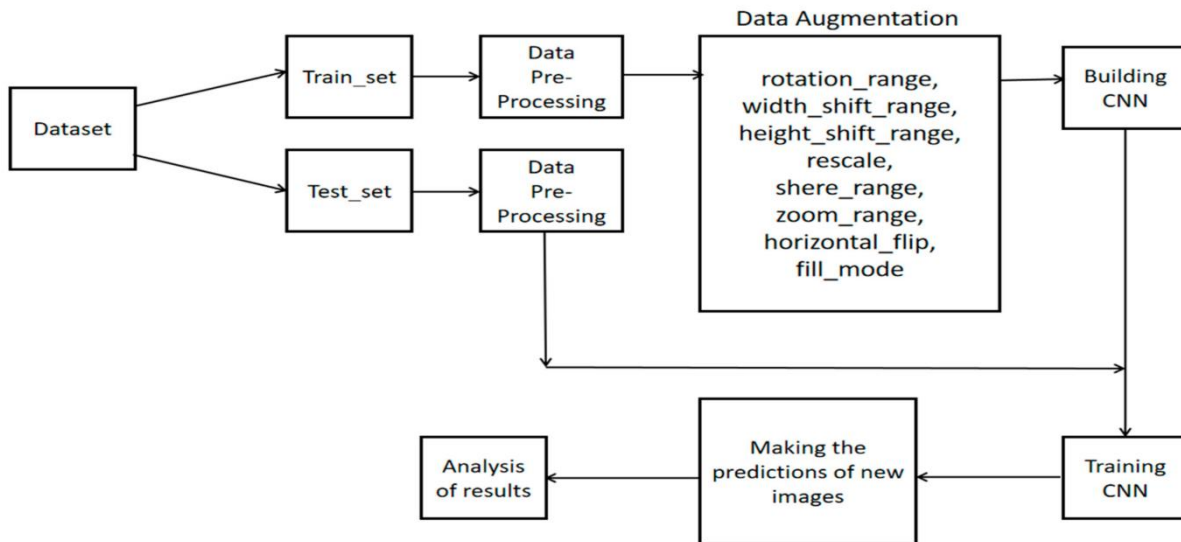
Precision agriculture: The system allows for targeted application of pesticides and other treatments, reducing the use of chemicals and improving the sustainability of agriculture.

Data-driven decision making: The data collected by the system can be used to make data-driven decisions about crop management and disease prevention.

#### **1. Methodology:**

Before proceeding with the character recognition process, it is necessary to pre-process the region of interest. There may be instances where two or more contours, such as in the case of the number "zero," completely enclose one another. If the internal contour is detected at the time of contouring process, it could be mistaken as a separate character, resulting in the identification of two different characters during the recognition process. To avoid this, we resize the image as needed during the pre-processing stage. Deskewing a licence plate: Skew is the amount of rotation required to bring a picture back into alignment with its horizontal and vertical axes. Degrees are used to quantify skew. De-skewing, It is the method of removing a skew by rotating a picture in the alternate direction by the identical amount as its skew. This causes the text edition to flow across the leaf rather than at a point of view, creating a picture that is aligned both inclined and upright. In our project, ratio and rotation is used to complete this phase ().

#### **1. System Architecture:**



1. Data Collection: The first step is to collect a large amount of data consisting of images of healthy plants and plants affected by different diseases. This data is used to train the CNN.
2. Data Pre-processing: The collected data is pre-processed to enhance the quality of the images and prepare them for input to the CNN. This may include resizing, cropping, and normalization.
3. Training the CNN: The pre-processed data is then used to train the CNN. The CNN consists of multiple layers, including convolutional layers, pooling layers, and fully connected layers. The convolutional layers are responsible for extracting features from the input images, while the pooling layers reduce the dimensionality of the features. The fully connected layers then use the features to classify the images as healthy or diseased.
4. Testing and Validation: Once the CNN is trained, it is tested on a set of validation data to evaluate its accuracy and fine-tune the model if necessary.
5. Deployment: Once the CNN is trained and validated, it can be deployed in a real-world setting for disease detection. The system can take input images of plants, process them through the CNN, and output a prediction of whether the plant is healthy or diseased.

## 2. Algorithm :

### Transfer learning -

Transfer learning is a technique in deep learning that utilizes a pre-trained model as a starting point for a new task instead of training a new model from scratch. In Convolutional Neural Networks (CNNs), transfer learning involves utilizing a pre-trained CNN model as a feature extractor for a new dataset and training a new classifier on top of the extracted features. The pre-trained CNN has already learned useful features from a large dataset like ImageNet, and these features can be transferred to other related tasks. To apply transfer learning in CNNs, one can remove the final classification layer from the pre-trained CNN and use the remaining layers to extract features from new images in the target dataset. These extracted features can be input to a new classifier, which is trained on the new dataset to predict the new set of classes. Using transfer learning in CNNs can significantly reduce the data and computational resources needed to train a new model from scratch, while also enhancing the model's accuracy on the new task. Transfer learning is a widely utilized technique in computer vision applications like object recognition, image classification, and segmentation.

### Convolutional Neural Network (CNN):

Convolutional Neural Networks (CNN) are a powerful tool for image recognition and processing, composed of different layers including convolutional and pooling layers, as well as fully connected layers. The convolutional layers use filters to extract features such as edges, textures, and shapes from the input image. The output of the convolutional layers is then passed through pooling layers to downsample the features and retain the most important information while reducing the spatial dimension. Finally, the output of the pooling layers is fed into fully connected layers to make predictions or classifications on the image. CNNs have achieved exceptional performance in image recognition and are commonly used in computer vision applications.

In the realm of CNNs, "original modeling" refers to the process of designing and training a new CNN architecture from scratch rather than using an existing pre-trained model or architecture.

Following are some steps we used in our project-

CNN (nn.Module) creates a class called CNN that is inherited from nn.Module, which is a PyTorch base class for neural network modules.

def \_\_init\_\_(self, K) initializes the CNN class and takes an argument K, which is the number of output classes.  
self.conv\_layers is a nn.Sequential module that contains the convolutional layers of the network. It consists of four sets of convolutional layers, each followed by a ReLU activation function and a batch normalization layer. Each set also has a max pooling layer that reduces the spatial dimensions of the output feature maps.  
self.dense\_layers is a nn.Sequential module that contains the fully connected layers of the network. It consists of two linear layers, each followed by a ReLU activation function and a dropout layer to prevent overfitting.  
def forward (self, X) defines the forward pass of the network. It takes an input tensor X and passes it through the convolutional layers, flattens the output, and passes it through the fully connected layers. The output is the predicted class probabilities.

## 2. Mathematical model -

Certainly! The equation  $(W - F + 2P) / S + 1$  is used to calculate the size of the output feature map in a convolutional neural network (CNN), given the size of the input feature map, the size of the filter (kernel), the amount of padding, and the stride.

Here's what each term in the equation means:

W: The size (width or height) of the input feature map.

F: The size (width or height) of the filter (kernel). This is the sliding window that is moved over the input feature map during the convolution operation.

P: The amount of padding that is added to the input feature map.

Padding is typically added to ensure that the spatial dimensions of the output feature map are the same as those of the input feature map, and to avoid losing information at the edges of the feature map during convolution. The amount of padding is usually specified in terms of the number of pixels added to each side of the input feature map. In this equation, we assume that the amount of padding is the same on both sides of the input feature map, so we multiply the padding size by 2.

S: The stride of the convolution operation. This determines how much the filter is shifted (or "strided") at each step during convolution. A stride of 1 means that the filter is shifted by 1 pixel at a time, while a stride of 2 means that the filter is shifted by 2 pixels at a time. +1: This is added to ensure that the output feature map has at least one pixel in each dimension.

The output of the equation is the size of the output feature map, which is calculated in each dimension (width and height) separately. For example, if the input feature map has a size of 32x32 pixels, the filter has a size of 5x5 pixels, the padding is 2 pixels on each side, and the stride is 1 pixel, then the size of the output feature map would be:

$$(32 - 5 + 2*2) / 1 + 1 = 32$$

So, the output feature map would also have a size of 32x32 pixels.

## IV. CONCLUSION

The agriculture industry plays a vital role in feeding the world's population, making early identification and detection of plant diseases crucial for crop production. Convolutional Neural Networks (CNNs) offer a promising solution for plant disease detection by using large datasets of plant images to train models to classify plants as healthy or diseased with high accuracy and efficiency. This can improve early detection and prevention of plant diseases, resulting in reduced crop losses and increased yield. However, it is essential to collect diverse and representative data, design effective CNN architectures, and fine-tune the model's using validation and testing sets to ensure accurate and reliable results. Ongoing research and development in this area can make a significant contribution to sustainable agriculture and food security.

## REFERENCES

- [1] Plant Disease Detection and Classification by Deep Learning. Muhammad Hammad Saleem 1 , Johan Potgieter 2 and Khalid Mahmood Arif 1.
- [2] Real-Time Detection of Apple Leaf Diseases Using Deep Learning Approach Based on Improved Convolutional Neural Networks. PENG JIANG, YUEHAN CHEN, BIN LIU, DONGJIAN HE, AND CHUNQUAN LIANG. 2019
- [3] Plant Disease Detection Using Machine Learning Techniques. Divyanshu Varshney, Burhanuddin Babukhanwala, Javed Khan, Javed Khan, Dr. Ashutosh kumarsingh. 2022
- [4] LEAF DISEASE DETECTION AND FERTILIZER SUGGESTION. Indumathi.R Saagari.N Thejuswini.V Swarnareka.R
- [5] Plant Pathology Disease Detection in Apple Leaves Using Deep Convolutional Neural Networks. Apple Leaves Disease Detection using EfficientNet and DenseNet. V V Srinidhi1, Apoorva Sahay2, K. Deeba3. 2021.



- [6] X. Zhang, Y. Qiao, F. Meng, C. Fan and M. Zhang, "Identification of Maize Leaf Diseases Using Improved Deep Convolutional Neural Networks" in IEEE Access (Volume: 6).
- [7] P. Jiang, Y. Chen, B. Liu, D. He and C. Liang, "Real-Time Detection of Apple Leaf Diseases Using Deep Learning Approach Based on Improved Convolutional Neural Networks" IEEE Access (Volume: 7).
- [7] U. P. Singh, S. S. Chouhan, S. Jain and S. Jain "Multilayer Convolution Neural Network for the Classification of Mango Leaves Infected by Anthracnose Disease" IEEE Access (Volume: 7).
- [8] M. A. Khan, S. S. Chouhan, A. Kaul, U. P. Singh, S. Jain "An Optimized Method for Segmentation and Classification of Apple Diseases Based on Strong Correlation and Genetic Algorithm Based Feature Selection" IEEE Access (Volume: 7).
- [9]. M.Sharif, M. A. Khan, Z. Iqbal, M. F.Azam, M. I. U. Lali and M. Y. Javed, "Detection and classification of citrus diseases in agriculture based on optimized weighted segmentation and feature selection," Computers and Electronics in Agriculture, vol. 150, pp. 220-234, 2018.
- [10] S. Dimitriadis, C. Goumopoulos, "Applying Machine Learning to Extract New knowledge in Precision Agriculture Applications," Panhellenic Conference on Informatics, pp. 100-104, 2008.
- [11] A. Akhtar, A. Khanum, S. A. Khan and A. Shaukat, "Automated Plant Disease Analysis (APDA): Performance Comparison of Machine Learning Techniques," International Conference on Frontiers of Information Technology, pp. 60-65, 2013. 4. K.P. Ferentinos, "Deep learning models for plant disease detection and diagnosis" Computers and Electronics in Agriculture, vol. 145, pp. 311-318, 2018