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An Android Application for Plant Disease Detection Using CNN Algorithm

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Abstract: *Plant diseases significantly affect both the quality and productivity of plants, underscoring the necessity of accurate identification for efficient management. The use of digital image processing, particularly deep learning, has emerged as a valuable tool in this field. In comparison to traditional methods, deep learning has demonstrated superior performance in detecting plant diseases. This has led to a noticeable shift in research focus towards harnessing deep learning for the study of plant diseases. This review delves into the challenge of plant disease detection, while also comparing it to conventional techniques. It examines recent advancements in deep learning-based approaches, categorizing them into classification, detection, and segmentation networks. The strengths and limitations of each approach are briefly discussed, along with an overview of commonly used datasets and an assessment of the effectiveness of previous studies.*

Keywords: *Deep Learning, Convolutional Neural Network, Plant Diseases, Classification, Object Detection, Segmentation, etc.*

I. INTRODUCTION

The timely detection of plant diseases is crucial for optimizing crop yield and minimizing economic losses within the agriculture sector. While manual disease identification by human experts is common, it suffers from drawbacks such as time consumption and susceptibility to errors. Additionally, reliance on costly methods and pesticides for disease control poses risks to both plant health and the environment. However, advancements in technology have opened avenues for automated disease detection through computer vision and artificial intelligence research. Image processing techniques play a significant role in agriculture, aiding in tasks such as weed detection, fruit grading, and the identification of plant disease infestations.

Deep learning methods, particularly convolutional neural networks (CNN), have gained prominence for their effectiveness in image-processing applications within agriculture. This study aims to investigate the potential of utilizing pre-trained CNN models for the early detection of plant diseases from raw images. The research will leverage a dataset from the Plant Village database and will encompass three primary phases: data acquisition, pre-processing, and image classification. By utilizing pre-trained CNN models, the study seeks to assess their efficacy in detecting plant diseases. The outcomes of this investigation hold promise for the development of more efficient and cost-effective approaches to managing plant diseases in agricultural settings. [1]

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Convolutional Neural Network

Artificial neural networks (ANNs) are a core component of deep learning, a field within machine learning and artificial intelligence that focuses on data analysis. In deep learning, models are trained to automatically extract features and classify data, enabling a wide array of applications such as computer vision, image classification, speech recognition, and video analysis. Convolutional Neural Networks (CNNs) stand out for their remarkable effectiveness in image processing and recognition tasks among the various types of deep learning algorithms.

The CNN architecture typically comprises four layers: the input image layer, convolutional layer, pooling layer, fully connected layers, and output layer. CNNs excel in evaluating graphical images and extracting crucial features through their multi-layered structure. As illustrated in Figure 1, CNNs demonstrate exceptional capability in detecting and categorising images with high accuracy, rendering them a preferred choice for image classification endeavours. [2]

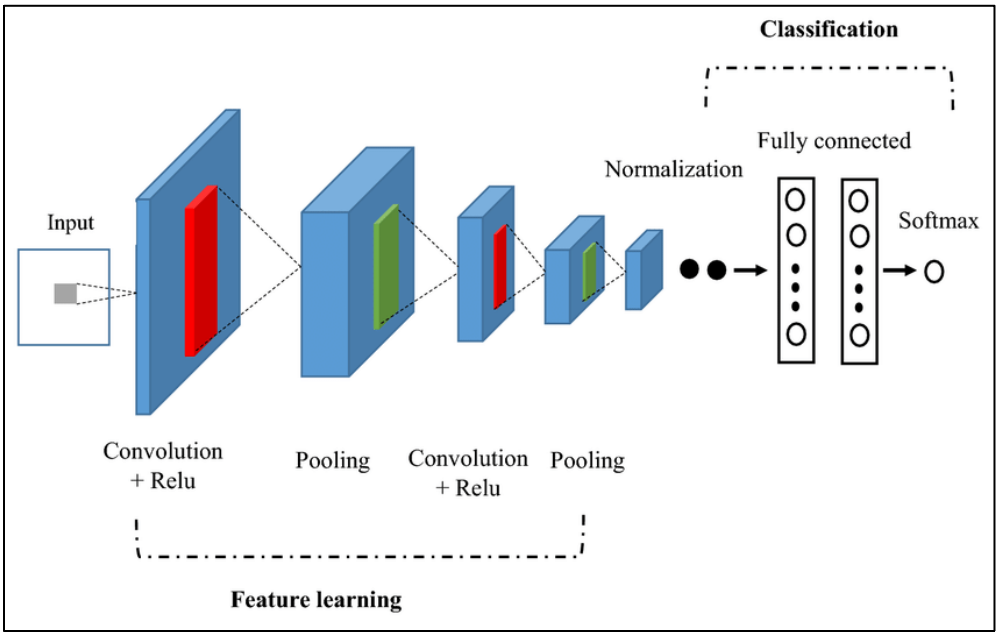

Figure 1: Illustration of Convolutional Neural Network Architecture

A. Convolutional Layer

The convolutional layer serves as a fundamental element in convolutional neural networks (CNNs), a widely utilized category of deep learning algorithms tailored for image and video processing tasks. Within CNNs, the convolutional layer operates by applying a series of trained filters (referred to as kernels or weights) to the input image. These filters traverse or convolve across the image, executing element-wise multiplication at each position before aggregating the outcomes to [3]

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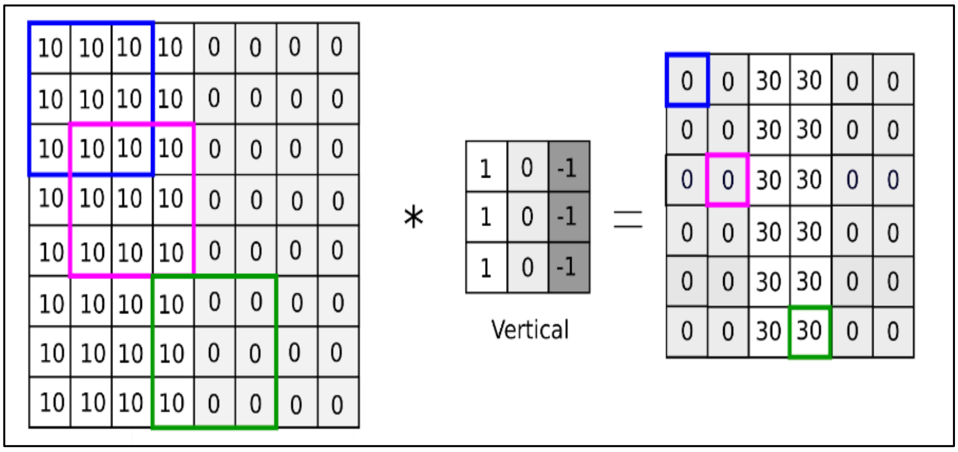

Figure 2: 8x8 Input and 3x3 Filter Operation of Convolution Layer. [21]

B. Pooling Layer

In convolutional neural networks (CNNs), the pooling layer plays a crucial role in down sampling the feature maps generated by the convolutional layers. This down sampling is advantageous as it aids in reducing the computational complexity of the network and helps prevent overfitting. The pooling layer operates by partitioning the input feature map into small regions, often referred to as pools, and replacing each region with a single representative value. Various pooling techniques exist, including max pooling and average pooling. In max pooling, the highest value within the pool becomes the output, whereas in average pooling, the average value is utilized. Pooling effectively reduces the spatial dimensions of the feature maps, thereby enhancing the efficiency of the network [20].

However, caution must be exercised in employing pooling, as excessive pooling may result in the loss of critical information from the input data. The size and operation of the pooling layer should be carefully chosen based on the specific requirements of the task and the characteristics of the data to optimize performance. [2]

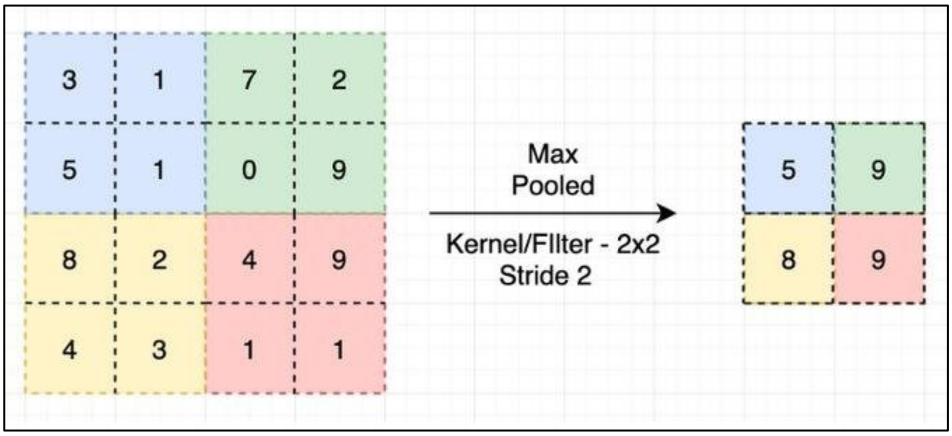

Figure 3: Pooling Operation [21]

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C. Activation Layer

The activation layer within a CNN serves as a critical component for introducing non-linear transformations to the output of convolutional or fully connected layers [19]. These transformations are essential for enabling the network to capture and learn complex relationships between the input and output data. The activation layer applies a mathematical function to each element of the output feature map, thereby introducing non-linearity into the network.

CNNs employ various activation functions, among which the Rectified Linear Unit (ReLU), Sigmoid, and Hyperbolic Tangent (tanh) are prominent examples. ReLU stands out as the most widely used activation function due to its computational efficiency and ability to expedite learning processes. It returns the input value if positive; otherwise, it returns 0. While Sigmoid and tanh activation functions have been historically utilized, they possess certain limitations. Sigmoid maps input to values between 0 and 1, which can be interpreted as probabilities, but it suffers from the vanishing gradient problem. Tanh, on the other hand, maps inputs to values between -1 and 1, making it suitable for outputs with negative values, albeit at a higher computational cost compared to ReLU. [17]

The selection of an appropriate activation function should consider the specific characteristics of the task and the data at hand. Experimentation with different activation functions is essential to determine the optimal choice for achieving desired performance outcomes. [4]

D. Fully Connected Layer

The fully connected layer within a convolutional neural network (CNN) is a critical component where each neuron is connected to every neuron in the preceding layer. Typically positioned at the end of the CNN, fully connected layers serve to map the output of convolutional and pooling layers to a desired output shape, such as classification or regression outcomes. The input to a fully connected layer comprises a vector obtained by flattening the output feature map of the preceding layer. For instance, if the output feature map has dimensions 4x4x64, the input to the fully connected layer would be a vector of length 1024 (4x4x64=1024). Each neuron in the fully connected layer is then linked to every element of this input vector. [5]

During training, the weights and biases of the fully connected layer are learned through backpropagation, akin to the convolutional and pooling layers. The output of the fully connected layer is computed by performing a weighted sum of the input, adding a bias term, and applying an activation function. While the Rectified Linear Unit (ReLU) is commonly used as the activation function in fully connected layers, alternatives such as sigmoid or tanh can also be employed. [8]

The determination of the number of neurons in the fully connected layer is a hyperparameter that requires user specification. This number is contingent upon the complexity of the problem at hand and the size of the input feature map. In general, a greater number of neurons enables the network to learn more intricate relationships, though an excessively large network may lead to overfitting [12]. Therefore, careful consideration must be given to striking a balance between model complexity and generalization capability.

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Objectives

1. To develop a prototype for a plant disease detection system.
2. To apply image processing techniques to identify the disease pattern.
3. Use deep learning algorithms to predict disease.
4. Use transfer learning techniques to predict disease.

II. LITERATURE REVIEW

K. Muthukannan and colleagues developed a system for identifying and categorizing spot infections in leaves using various machine learning algorithms. They utilized LVQ (Learning Vector Quantization), FFNN (Feed Forward Neural Network), and RBFN (Radial Basis Function Networks) to diagnose diseased plant leaves by analyzing form and texture data from leaf images. Their simulation demonstrated the effectiveness of the proposed system, suggesting its potential for improving crop quality in the Indian economy. [7]

Malvika Ranjan and colleagues focused on identifying cotton leaf diseases by capturing images and extracting color data, such as HSV features, from segmentation results. They trained an artificial neural network (ANN) using selected feature values to discriminate between healthy and diseased samples. Their study proposed a method for early and reliable identification of cotton leaf illnesses through image data processing methods and ANN. [9]

Syafiqah Ishakais and colleagues aimed to classify healthy and diseased leaves of medical plants by acquiring and analyzing data from leaf photos. They employed an algorithm for adjusted contrast, segmentation, and feature extraction to extract pictures and obtain data from the image processing approach. Artificial Neural Networks, including multilayer perceptron and radial basis function RBF, were used for leaf classification, with the RBF network outperforming the MLP network in their experiment Srdjan Sladojevic and colleagues proposed a new method for constructing a crop diseases recognition model based on plant image classification and deep convolutional networks. [6]

They utilized the deep learning framework Caffe to train deep CNNs, achieving precision between 91% and 98% on average 96.3% for separate class tests, in their experimental result Emanuel Cortes and colleagues utilized deep neural networks and semi-supervised algorithms to distinguish crop species and disease status using a publicly available dataset of photos of ill and healthy plants. Their unlabeled data experiment, rs-net, achieved a detection rate of 1e-5 and scored more than 80% accuracy in the training phase in less than 5 epochs. [10]

Konstantinos P. Ferentinos and colleagues developed CNN models for crop disease identification and diagnosis using basic leaf pictures of healthy and sick plants. Their top-performing model achieved a success rate of 99.53%, making it a valuable tool for early detection of plant diseases. [13]

Serawork Wallelign and colleagues demonstrated the viability of CNNs for crop disease identification in soybeans using the LeNet architecture. Their model achieved a classification accuracy of 99.32% on a dataset comprising samples of healthy and diseased soybean leaves captured in unstructured settings. [14]

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Alvaro Fuentes and colleagues investigated the real-time recognition of tomato plant pests and diseases using deep learning meta-architectures such as Faster R-CNN, R-FCN, and SSD, coupled with deep feature extractors like VGG net and Residual Network. Their systems achieved high accuracy by locally and globally categorizing and extracting features, effectively reducing false positives during training. Unnamed authors developed a deep CNN model based on AlexNet architecture to accurately identify apple leaf diseases. [15] Their model achieved a total accuracy of 97.62%, with significantly reduced parameters compared to AlexNet and enhanced accuracy with produced pathological pictures. Prasanna Mohanty and colleagues developed a deep convolutional neural network for detecting various crop diseases with an accuracy of 99.35% on a held-out test set. Despite achieving high accuracy, they noted the need for a larger collection of training data to further increase overall accuracy. [22]

III. DATASET DESCRIPTION

The dataset encompasses roughly 75,000 images, showcasing various instances of plant leaf diseases across different species. These include 2 types of potato leaf diseases, 3 types of apple leaf diseases, 4 types of corn leaf diseases, 3 types of grape leaf diseases, 1 type of cherry disease, 3 types of cotton leaf diseases, 1 type of peach leaf disease, 1 type of bell pepper leaf disease, 2 types of rose leaf diseases, 4 types of tomato leaf diseases, and 1 type of strawberry leaf disease. [18]

Furthermore, the CNN model is integrated into an Android application for practical deployment. All images within the dataset were utilized for both training and testing purposes, with multiple images captured directly from field observations. Each plant CNN model underwent training for 15 epochs, employing a batch size of 32. [11] The experiments were conducted using an ASUS ROG Ryzen 7 processor with a memory size of 16GB.

IV. METHODOLOGY

A schematic diagram depicted in Fig. 4 illustrates the flow of the Input Dataset, Image Acquisition, Image Pre-processing, and Classification stages.

A. Image Acquisition

The dataset utilized in this study originates from the New Plant Village dataset, which serves as the source of the image collection employed for algorithm training. The plant disease images were retrieved from this source using a Python script. The dataset comprises approximately 65,000 images distributed across 11 distinct categories of plant types and diseases. [11]

B. Image Pre-processing

The pre-processing of images involves resizing them to reduce their dimensions and cropping them to fit a designated input size. Furthermore, adjustments are made to enhance and standardize the colour scale of the images. In this research, coloured photographs with a resolution of 256x256 pixels are processed and resized. [11]

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C. Classification

The classification process employs fully connected layers for categorization, while convolutional and pooling layers are utilized for feature extraction. This procedure involves determining the type of plant disease and classifying the plant leaves based on their diseased or healthy status. [11]

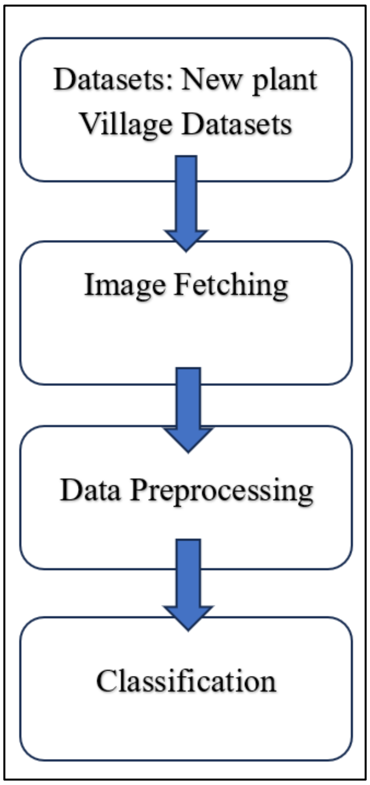

Figure 4: Plant Leaf Disease Recognition Methodology

V. RESULTS AND ANALYSIS

The model achieved a remarkable accuracy rate of 98% after 10 epochs during the training phase. Subsequently, when tested against random photographs depicting various plant species and diseases, the model exhibited its highest accuracy level of 100%. Fig illustrates the visualization of plots depicting training and validation accuracy, providing insights into the model's proficiency in detecting and recognizing plant illnesses. Furthermore, the figure showcases a 100% accuracy rate in recognizing a healthy plant leaf in the left image and identifying early blight disease with 100% accuracy in the right image. Similarly, the figure demonstrates a 100% confidence rate in diagnosing cedar apple rust disease in the right image, juxtaposed with 100% accuracy in recognizing a healthy plant leaf in the left image. Fig. depicts a 100% accuracy rate in identifying common rust disease in the left image while achieving a 98% accuracy in recognizing a healthy plant leaf in the right image.

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Moreover, the figure illustrates a 100% confidence rate in detecting black rot disease in the left image, alongside 100% accuracy in recognizing a healthy plant leaf in the right image. Finally, Fig. exhibits a 100% accuracy rate in diagnosing bacterial spot disease in the right image, complemented by 100% accuracy in recognizing a healthy plant leaf in the left image.

A. Potato

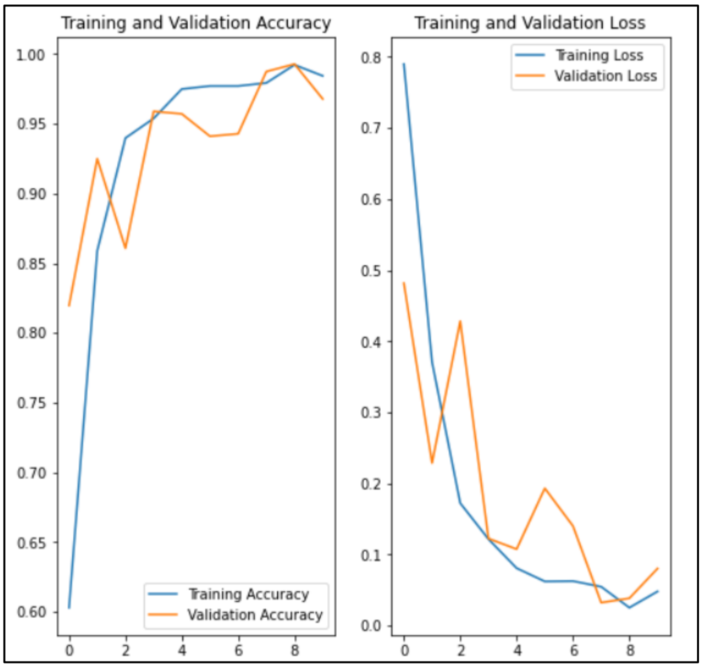

Figure 5: Potato Training and Validation Graph for Accuracy and Loss

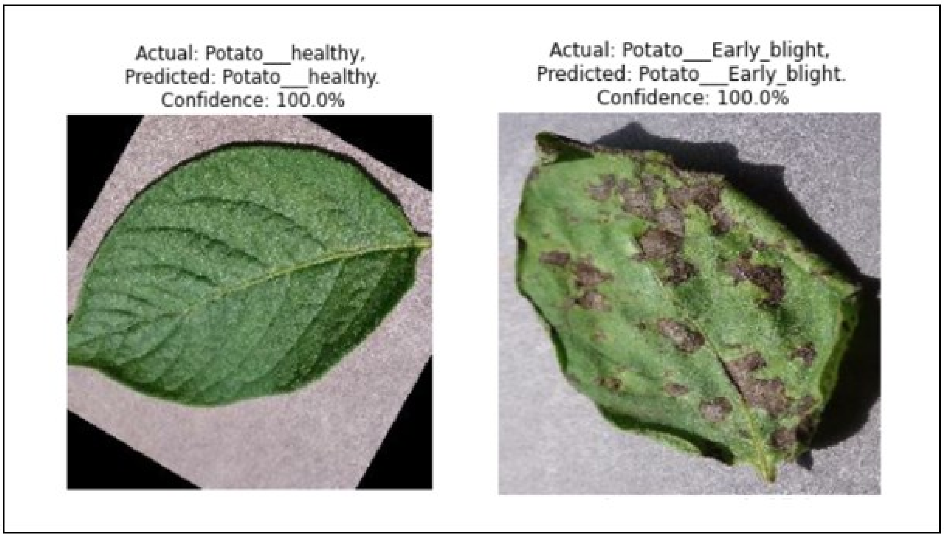

Figure 6: Result of detection and recognition of a Potato plant leaf infected with early blight disease with 100% confidence and predicted a healthy plant leaf on the left image with 100% confidence.

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B. Apple

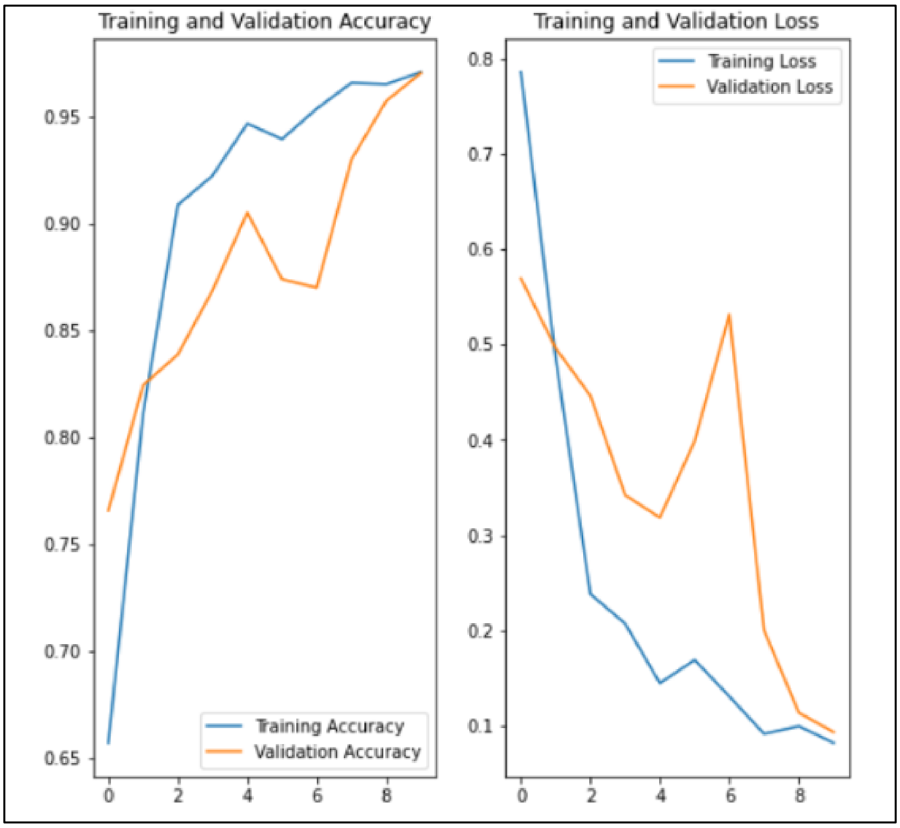

Figure 7: Apple Training and Validation Graph for Accuracy and Loss

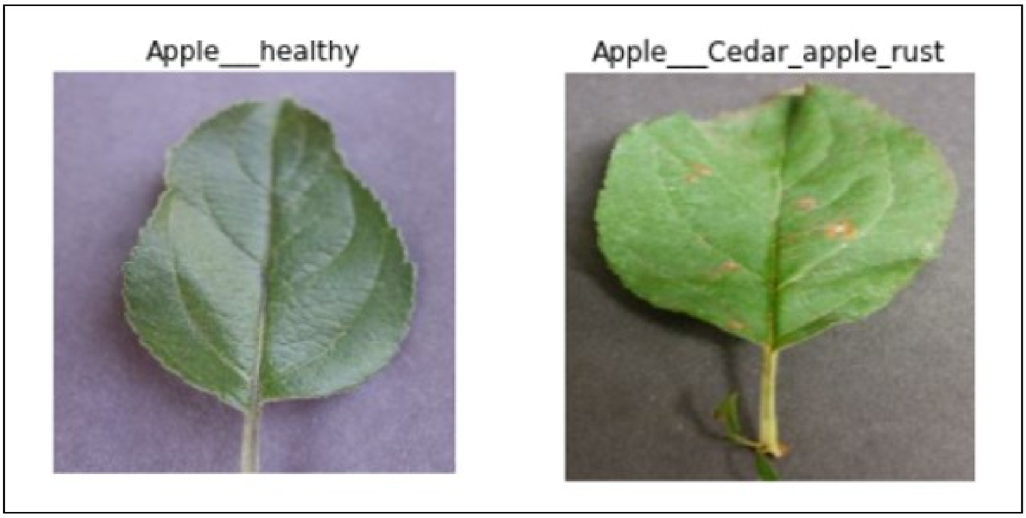

Figure 8: Result of detection and recognition of an apple plant leaf infected with a cedar apple rust disease on the left image with 100% confidence and predicted a healthy leaf on the left image.

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C. Cotton

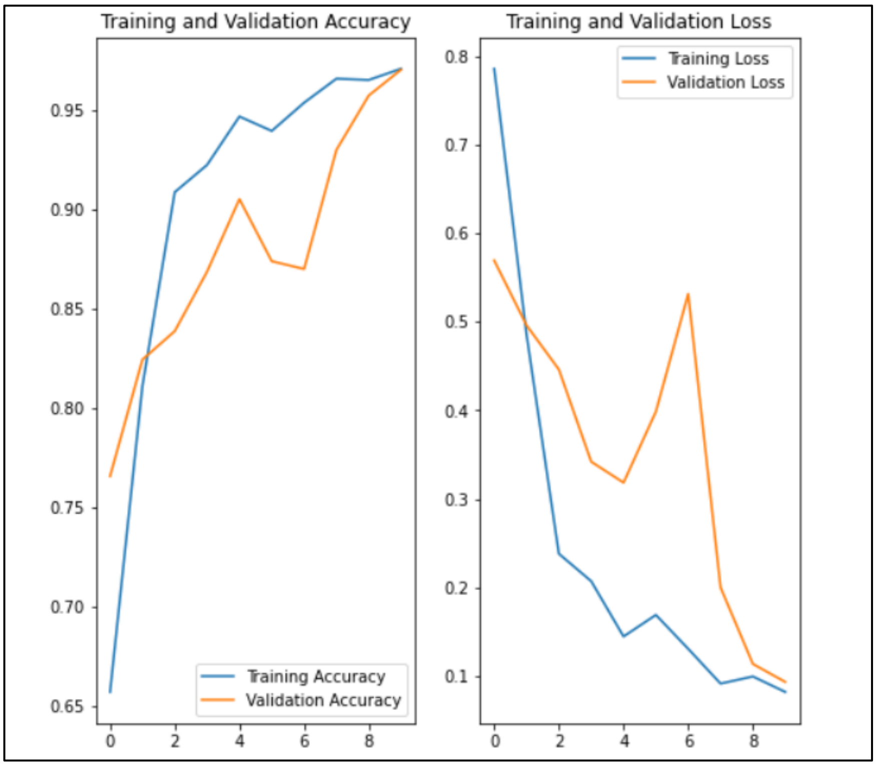

Figure 9: Apple Training and Validation Graph for Accuracy and Loss

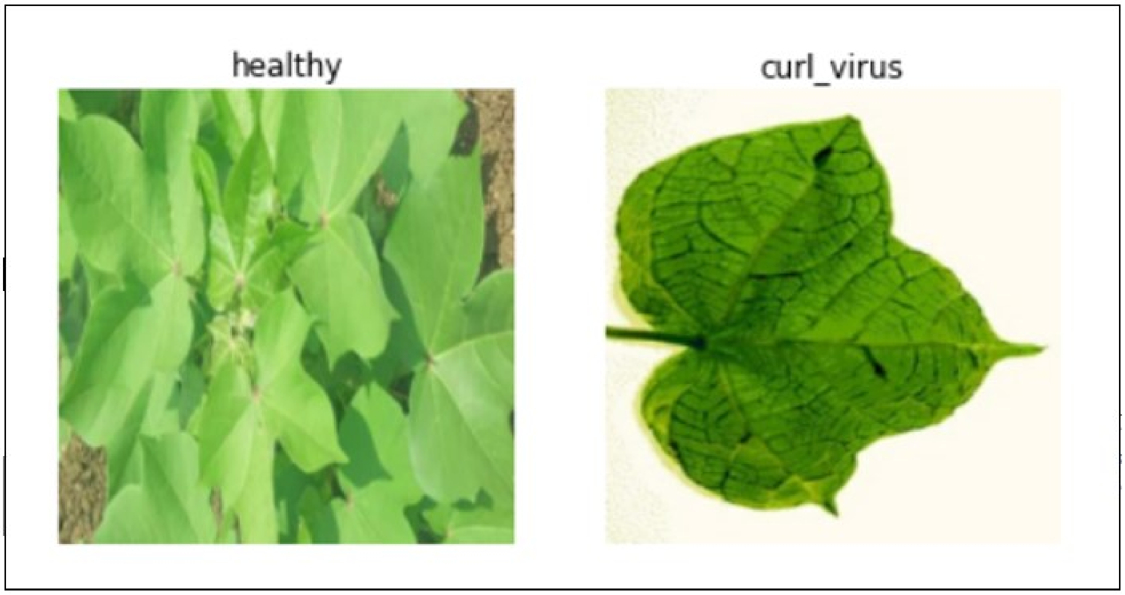

Figure 10: Result of detection and recognition of an apple plant leaf infected with a cedar apple rust disease on the left image with 100% confidence and predicted a healthy leaf on the left image.

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VI. CONCLUSION

The agricultural sector plays a crucial role in sustaining populations worldwide by providing essential food crops. Early detection and identification of plant diseases are imperative for ensuring agricultural productivity. This study successfully employed a convolutional neural network (CNN) to accurately identify and detect 17 distinct plant species and associated illnesses. The trained model can be utilized for real-time analysis of plant photographs, facilitating prompt disease diagnosis. To enhance the efficacy of future models, it is recommended to expand the dataset to encompass a wider range of plant species and diseases. Additionally, experimentation with different CNN architectures, learning rates, and optimizers can further refine the model's performance and accuracy. With an impressive accuracy rate of 96.5%, the proposed approach offers a valuable tool for farmers in promptly identifying and managing plant diseases, thereby safeguarding crop yields, and ensuring food security.

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