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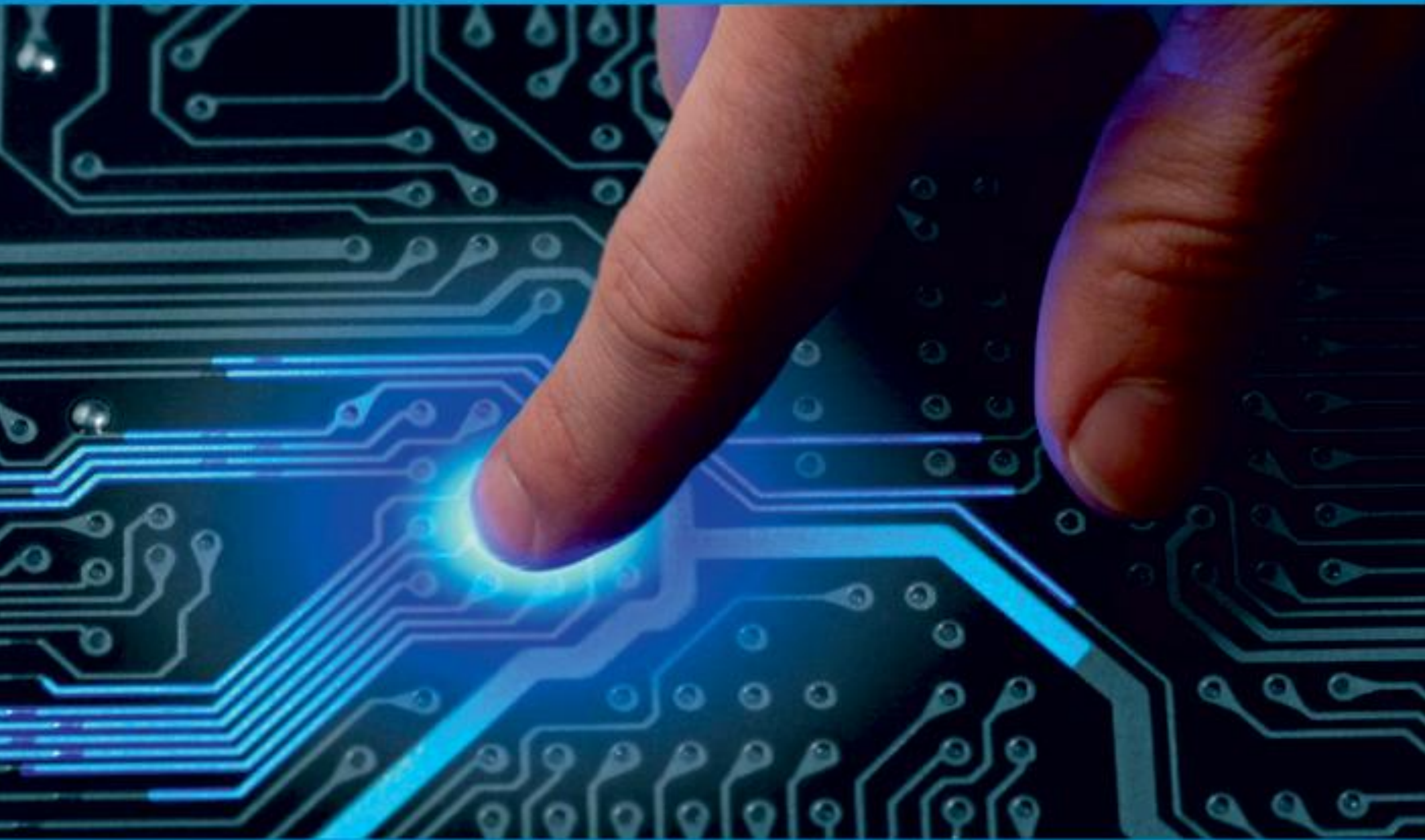

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Deep Learning Based Tomato Leaf Disease Detection for Smart Farming

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ABSTRACT: Tomato cultivation has a major role in global agriculture, contributing to both food security and economic stability. Still, tomato plants are susceptive to various diseases, which can specially reduce yield and quality. Plant disease early detection and treatment depend more and more on automatic disease identification and categorization technologies. In this paper, we present a Deep Learning based approach for tomato leaf diseases classification using VGG16 Convolutional Neural Network architecture. The VGG16 model is well-known for its superior picture categorization ability, A data set is used to train the VGG16 that includes healthy tomato leaves and leaves that are contaminated with common diseases like Early Blight, Late Blight, Leaf Mold, and Bacterial Spot. The dataset used in training and assessment comprises a varied assortment of high-resolution images acquired from various sources, guaranteeing the resilience and adaptability of the suggested model. Our utilization of data augmentation methods aims to improve the model's capacity to address variations in leaf characteristics, such as alterations in lighting, background complexity, and leaf positioning. Through experimental findings, we have validated the efficacy of our approach in precisely categorizing tomato leaf diseases with remarkable recall rates and precision. Comparative evaluations against leading techniques highlight the superior classification performance and computational efficiency of the VGG16-based model.

KEYWORDS: Deep Learning, Neural Network, Farming, Leaf disease detection, Image recognition.

I. INTRODUCTION

Tomato holds significant economic value as a vegetable crop worldwide, providing essential nutrients and contributing significantly to world agriculture production and trade. However, the cultivation of tomatoes faces numerous challenges, among which the prevalence of diseases ranks as a primary concern. Plant diseases, especially those affecting leaves, result in substantial losses in yield and diminish crop quality, leading to significant economic repercussions for farmers and threatening food security.

Traditional methods of disease identification and recognition often rely on visual inspection by agricultural experts, which can be time-consuming, labor-intensive, and prone to subjective interpretation. Moreover, the identification of illnesses is crucial for effective management and mitigation strategies, making the advancement of self-operated and accurate disease classification systems imperative.

In the recent years, advancements in artificial intelligence and computer vision have paved the way for the application of deep learning techniques in agricultural contexts, including the automatic plant identification and categorization diseases. Convolutional Neural Networks (CNNs), A class of deep learning models, have shown remarkable performance in image classification tasks, making them well-suited for identifying patterns and features indicative of plant illnesses in digital images.

This research aims to leverage the ability of CNNs, particularly the VGG16 architecture, for the indexing of a tomato leaf diseases. By training the model on a diverse dataset containing images of healthy tomato leaves and leaves affected by common diseases such as early blight, late blight, leaf mold, and bacterial spot, we seek to design a robust and accurate classification system.

The suggested system has potential for revolutionizing disease management practices in tomato cultivation by providing farmers with a fast, reliable, and non-destructive means of disease diagnosis. By enabling early detection and targeted intervention, the system has the potential to minimize yield losses, optimize resource utilization, and contribute to sustainable agricultural practices. Moreover, the scalability and adaptability of the framework make it well-suited for

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integration into precision agriculture frameworks and agricultural IoT (Internet of Things) systems, facilitating real-time monitoring and decision-making.

II. BACKGROUND STUDY

Before the advent of automated systems depends on deep learning algorithms like VGG16, tomato leaf disease categorization primarily relied on manual inspection by agricultural experts. In these traditional systems:

1. **Manual Inspection:** Agricultural experts or field workers visually inspected tomato plants for symptoms of diseases. That involved examining individual leaves for discoloration, lesions, spots, or any other abnormalities indicative of disease.
2. **Visual Identification:** Based on their expertise and knowledge of plant pathology, experts identified and classified diseases by visually comparing observed symptoms with reference images or descriptions of known diseases.
3. **Limited Scale and Accuracy:** Manual inspection methods were time-consuming and labor-intensive, limiting the scale at which disease detection could be performed. Furthermore, the exactness of disease identification depended heavily on the knowledge of the individuals conducting the inspection, leading to potential errors and inconsistencies in classification.
4. **Challenges:** Manual inspection techniques encountered difficulties including human error, subjective analysis of symptoms, and the incapacity to identify diseases in their initial phases when symptoms are not easily observable.
5. **Resource Intensive:** Employing skilled personnel for visual assessment by hand incurred significant costs for agricultural operations, especially for large-scale farming operations.
6. **Delayed Response:** Due to the time required for manual inspection and diagnosis, responses to disease outbreaks or infections were often delayed, leading to potential crop losses and reduced yields.
7. Overall, while manual inspection served as the primary method for the purpose of identifying diseases in the past, it was limited in scalability, accuracy, and timeliness. The transition to automated systems depends on deep learning algorithms like VGG16 represents a significant advancement, offering faster, more accurate, and scalable solutions for tomato leaf disease categorization and management.

III. METHODOLOGY

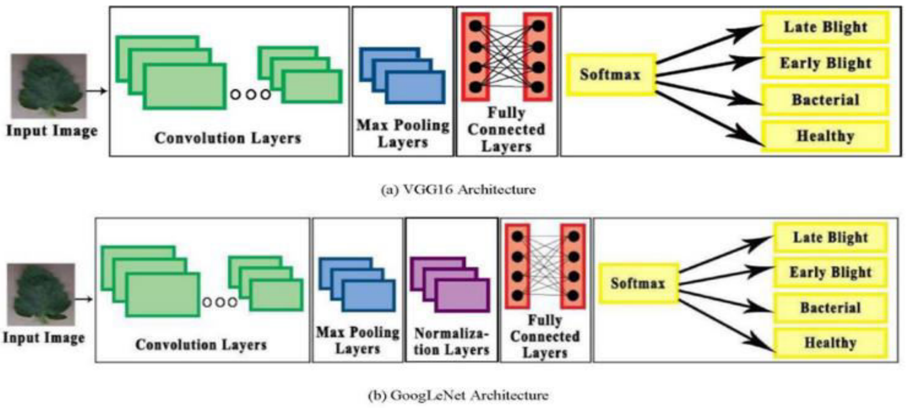

Fig 1: VGG16 Architecture V/S GoogLeNet Architecture

1. Data Collection and Preprocessing:

a) **Dataset Compilation:** Collect a wide range of data containing pictures of tomato leaves affected by various illnesses such as early blight, late blight, leaf mold, bacterial spot, along with images of healthy tomato leaves.

b) **Data Augmentation:** Use strategies such as rotation, flipping, scaling, and shifting to augment the dataset, increasing its size and diversity.

c) **Data Split:** In order to effectively train, validate, and assess the effectiveness of the model, it is necessary to divide the dataset into distinct training, validation, and testing sets.

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2. Model Selection:

a) **VGG16 Architecture:** Choose the VGG16 convolution neural network architecture as the foundational model for disease classification.
b) **Transfer Learning:** Utilize transfer learning by initializing the VGG16 model with pre-trained weights on ImageNet, enabling the model to leverage knowledge learned from a large-scale image classification task.

3. Fine-tuning and Training:

a) **Model Adaptation:** Modify the VGG16 model architecture by removing the fully connected layers and replacing them with custom layers suited for the categorization of diseases.
b) **Freezing Pre-trained Layers:** Freeze the weights of the pre-trained layers to stop them from being updated during training, ensuring that the model retains previously learned features.
c) **Training:** Train the modified VGG16 model over the training dataset using techniques such as stochastic gradient descent (SGD) or Adam optimizer with appropriate learning rates.

4. Model Evaluation:

a) **Validation Set Performance:** Examine the trained model's performance on the validation set to determine its ability to generalize to new data and prevent overfitting.
b) **Hyperparameter Tuning:** Fine-tune hyperparameters such as learning rate, batch size, and dropout rate to optimize the model's performance.

5. Model Testing and Evaluation:

a) **Testing Set Evaluation:** Measure The precision of disease classification by testing the final trained model on the set of tests.
b) **Model Deployment and Future Work:**

Deployment: The trained model may be deployed as a desktop application to facilitate real-time classification of tomato leaf diseases, empowering farmers to efficiently identify and address crop diseases.

IV. IMPLEMENTATION

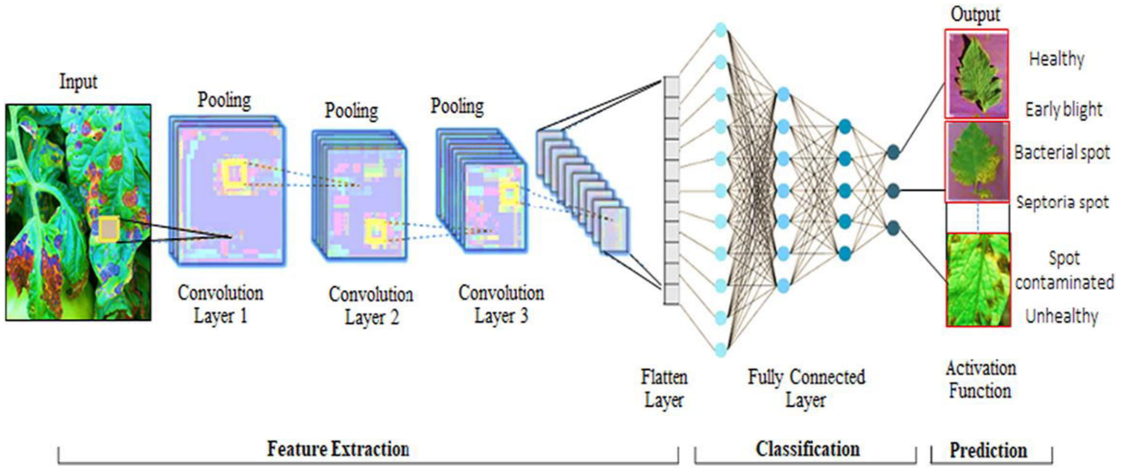

Fig 2: Convolutional Neural Networks (CNNs) architecture

A. Dataset

The proposed model has undergone training and evaluation using the state-of-the-art Plant Village dataset, which includes 10735 photos in total showcasing tomato leaves. This dataset has been divided into separate testing and training segments sets, with the training set containing 70% of the total images and the testing set encompassing 30% of the images from the dataset.

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B. Image Pre Processing

The dataset comprises RGB images of varying sizes. Prior to being fed two preprocessing stages are entered into the CNN. carried out on the leaf images. Firstly, the pictures are scaled down to match the input layer dimensions of the CNN. The dimensions are standardized across different architectures, with the images being resized to 224x224.

C. Transfer Learning

The practice of enhancing the learning of new information by using knowledge gained from a preliminarily completed source task is known as transfer learning. In transfer learning, retraining the model using a different dataset after the algorithm has generally been pre-trained with enough information samples. Each subcaste in the CNN architecture has a distinct purpose, similar as segmentation, point birth, edge discovery, and so forth. The CNN architecture consists of many layers. Convolution layers, Max- pooling layers, the ReLU activation function, completely connected layers, and the Softmax subcaste are all part of the VGG16 architecture.

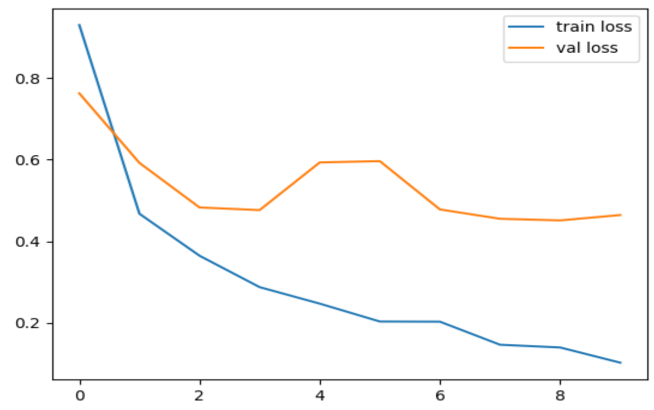

Fig 3: Train & validation losses

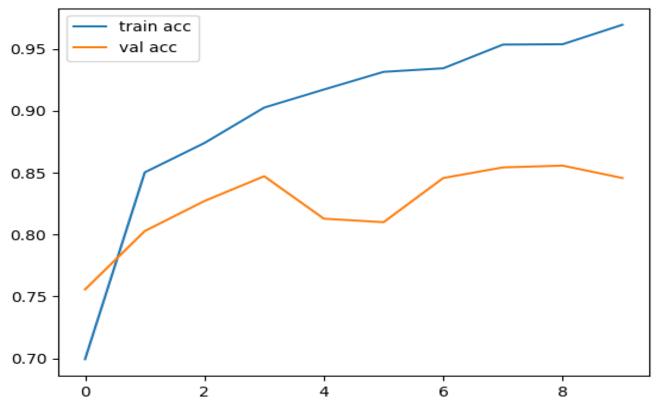

Fig 4: Train & validation Accuracy

V. RESULT

We have trained the dataset containing different types of skin disease classes by pre-processing and feeding the pre-processed dataset to the deep learning algorithm, once the model completes the training process the trained model will be saved for future input classification where user will browse the skin image and feed input, the fed image will be pre-processes and Provided to the trained model, the model will classify the disease type, depends on the classified results a list of doctors will be displayed to the user who will treat such disease so that the patient can’t take treatment.

VI. CONCLUSION

The developed tomato leaf disease identification model, utilizing the VGG16 architecture, demonstrates promising performance in accurately identifying various diseases affecting tomato plants. Through evaluation metrics such as accuracy. The model showcases robust classification capabilities. Class-specific analysis uncovers disparities in accuracy across various disease categories, pointing up possible places for more development. While the model effectively leverages the VGG16 architecture, future enhancements could focus on hyper parameter tuning and data augmentation to optimize performance further. Overall, the model represents a significant development in the automation of disease identification in tomatoes, suggesting potential improvements in crop management practices and yield.

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