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# FUNGAL INFECTION IDENTIFICATION IN PLANTS AND RECOMMEND ORGANIC FERTILIZER USING DEEP LEARNING

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***Abstract:*** **Fungal infections in plants pose a significant threat to global agriculture, leading to substantial economic losses and food security concerns. Traditional methods for detecting and identifying fungal infections are often time-consuming, labor-intensive, and require expert knowledge. Recent advancements in deep learning (DL) offer promising solutions to these challenges by providing automated, accurate, and efficient identification systems using CNN and Mobile Net.**

***Keywords***- **Deep learning, Fungal Infection, CNN and Mobile Net.**

## I. INTRODUCTION

More than seventy percent of people in India work in farming. Fungal infections in plants pose significant threats to agriculture, forestry, and biodiversity. Identifying these infections accurately and promptly is crucial for preventing production loss, effective disease management and control. Traditional methods for detecting fungal infections in plants involve visual inspections, laboratory tests, and molecular techniques, which can be time-consuming, labor-intensive, and sometimes inaccurate due to human error. With advancements in technology, deep learning (DL), a subset of machine learning, has emerged as a promising tool for the identification of fungal infections in plants. Fungal pathogens are responsible for a wide range of plant diseases, affecting leaves, stems, roots, and fruits. Common fungal diseases include powdery mildew, rusts, blights, and smuts, which can lead to reduced crop yields and quality, economic losses, and food security issues. Early and precise identification of these infections is essential for implementing timely and effective treatment strategies, reducing the spread of the disease, and minimizing damage.

In this task, we developed an approach to detect plant fungal infection from leaf images. Image analysis is a subset of signal processing that extracts image attributes and useful information. Machine learning is a branch of AI that acts autonomously or is given instructions to perform certain tasks. The primary goal of artificial neural networks is to comprehend training data and incorporate it into methods that are valuable to humans.

It has a large amount of training data to help you make better decisions and predict the correct outcome. They are classified according to characteristics such as leaf color, degree of leaf damage, extent of leaf damage and texture. In this study, we examined different image metrics or features for detecting different plant leaf fungal infection to achieve the highest accuracy.

The identification of plant fungal infection used to be performed by experts using chemical techniques or physical examination of leaf areas. This necessitates an extensive staff of specialists and ongoing plant surveillance, both of which are expensive on huge farms. In such cases, the proposed approach is suitable for monitoring large crop fields. Comprehensive diagnosis of disease can be made simply by observing signs on plant leaves, making the process easier and less expensive. The proposed plant disease identification solution uses quantitative neural networks and image analysis algorithms, resulting in less computational load and shorter prediction time than existing deep learning-based systems.

Deep learning for leaf disease detection is an approach to identify and diagnose plant leaf fungal infection using neural network technology. The technique has drawn a lot of interest recently because, by assisting farmers in early detection and treatment of crop illnesses, it has an opportunity to increase agricultural output and decrease the use of pesticides. Plant diseases are usually detected by expert inspection, which can be expensive and error prone. Advances in machine learning and computer vision approaches have made it possible to develop machine learning algorithms that can identify and classify crop diseases from leaf photographs.

Deep learning techniques such as convolutional neural networks (CNNs) are widely used for leaf fungal infection detection because they can automatically learn important traits from photographs. The algorithm used is trained on a huge dataset of annotated photographs of healthy and diseased leaves of plants to learn how to recognize the features and traits that distinguish leaf health from diseased leaves. . Once trained, deep learning algorithms can reliably detect and diagnose diseases affecting plant leaves by analyzing photos of plants. When the technology detects signs of disease, it sends real-time alerts to farmers, helping them take immediate action to prevent the infection from spreading to other crops.

Deep Learning (DL) offers promising solutions for the accurate and timely identification of fungal infections in plants. By leveraging DL techniques, particularly Convolutional Neural Networks (CNNs) shown great potential in image analysis tasks due to their ability to automatically extract and learn hierarchical features from raw data. In the context of plant pathology, DL models can be trained to identify and classify fungal infections from images of plant tissues with high accuracy and efficiency.

## II. LITERATURE SURVEY

The appearance, shape, color and other features of lesions are often extracted using conventional computer vision algorithms for identifying plant diseases. This method has low detection efficiency as it relies on a thorough understanding of agricultural diseases by a team of experts. With rapid progress in artificial intelligence technology, many scientists have recently conducted extensive research using deep learning software to improve the accuracy of plant disease detection [1]. Many of the methods currently used to analyze plant diseases are based on disease taxonomy [3].

Three CNN systems were developed using the transfer learning method of Selvaraj et al. retrained. [3, 9]. To make accurate predictions, we used advanced transfer learning to form a network using a learned disease detection model

Identification of diseases and pests in images of tomato plants taken at different camera resolutions was reported by Fuentes et al. I suggested. [4, 7]. A series of he used CNN object detectors and deep learning architectures. We used local and global class annotations and data augmentation to improve training accuracy and reduce false alarms. An extensive dataset on tomato diseases was used for extensive training and testing. The algorithm successfully identified nine different pests and diseases using complex settings.

We used Mohanty et al. [5] Google Net and Alex Net to classify 54,306 plant leaf images from the Plant Village dataset as healthy or unhealthy. The results showed that GoogleNet has slightly greater average classification influence than AlexNet. A fundamental method of using smartphones to detect disease in horticultural crops is to use deep learning to build models on growing and freely accessible photographic datasets.

A state-of-the-art technique based on deep latent neural networks was published by Picon et al. already used. [6] Used for diagnosis of numerous plant diseases under real working conditions. There are several suggestions for improving early disease detection. Data showed that her AuC values for all assessed diseases were above 0.80. A key factor in the fall in agricultural productivity is plant diseases. [14] The majority of farmers find it challenging to monitor and identify crop illnesses. To reduce future losses, the disease must be detected early. In this study, leaf diseases of tomato plants are identified using Fuzzy-SVM, CNN, and R-CNN. Photographs of six infected leaves from tomatoes and leaves from healthy specimens were utilized to verify the findings. Image scaling, color thresholding, fill techniques, ternary patterns of gradient positions, and Zernike moment functions are all used in photo training. Disease types are classified using the R-CNN algorithm. Classification techniques fuzzy SVM, CNN, and R-CNN are examined and compared to find the best algorithms for predicting plant diseases. [9] In this paper, we suggest a solution for the detection of pomegranate fruit disease (bacterial blight) and also the solution for that disease after detection is proposed. Bacterial Blight need to control at primary stages otherwise it will lead to economic loss. Web-based system used to help non experts in identifying fruit diseases, based on the picture representing the symptoms of the fruit.The economy has the greatest impact on agricultural production. Crop diseases are becoming more and more prevalent in agricultural areas, and the above causes make crop diseases more identifiable. The identification of plant diseases is becoming increasingly important in vast and diverse plant areas. [13] Farmers face great challenges when switching from one disease management principle to another. A traditional identification strategy is to find tomato leaf diseases so that they can be observed by an expert. Without effective control, plants are severely damaged and the quality of plant products is reduced. Disease detection through mechanized approaches and approaches is successful and creative because it saves enormous labor in large-scale agriculture. We can recognize signs of plant illnesses in their earliest phases, when they initially develop on the leafy parts of the crops. Using this study, we can determine the technique utilized for photo segmentation and automated categorization in the identification of leaf diseases in plants. It also includes different illness categorization methods of operation that are utilized for identifying illnesses in crops

[2] P.R. Rothe and RV Kshirsagar published "Identification of cotton leaf diseases using pattern recognition techniques" using snake segmentation and Hu moments as features. Active contour models are used to limit survival within infected regions, and BPNN classifiers address different classes of problems. The average classification rate is 85.52%. [8] "Visual-based automated

diagnosis of banana bacterium and black sigatoka" was proposed by Godliver Owomugisha, John A. Quinn, Ernest Mwebaze, and James Lwasa. A color histogram is taken and converted from RGB to HSV and then to L*a*b. A max tree is constructed using peak components, 5 shape attributes are used for classification, and area under curve evaluation is used. They used nearest neighbors, decision trees, random forests, hyperrandom trees, naive Bayes, and SV classifiers. A highly random tree produces very high scores across seven classifiers, providing real-time information and adding versatility to the application.

[6] uan Tian, Chunjiang Zhao, Shenglian Lu and Xinyu Guo, "SVM-based Multiple Classifier System for Recognition of Wheat Leaf Diseases", Color features are encoded in HIS in RGB, and seven invariant moments are used as shape parameters Used by GLCM. They used his SVM classifier with MCS for offline disease detection in wheat plants.

## III. METHODOLOGY

**Tools Used:**

The whole system is implemented using python programming language in visual studio and Jupyter notebook.

**Workflow:**

I used Python, Visual Studio, and Jupyter notebook to finish the entire project. The collected information is examined, summarized, and all zero values are eliminated. Here we are using CNN, Mobile Net for training the data. The following figure shows the proposed architecture it tells about work flow.

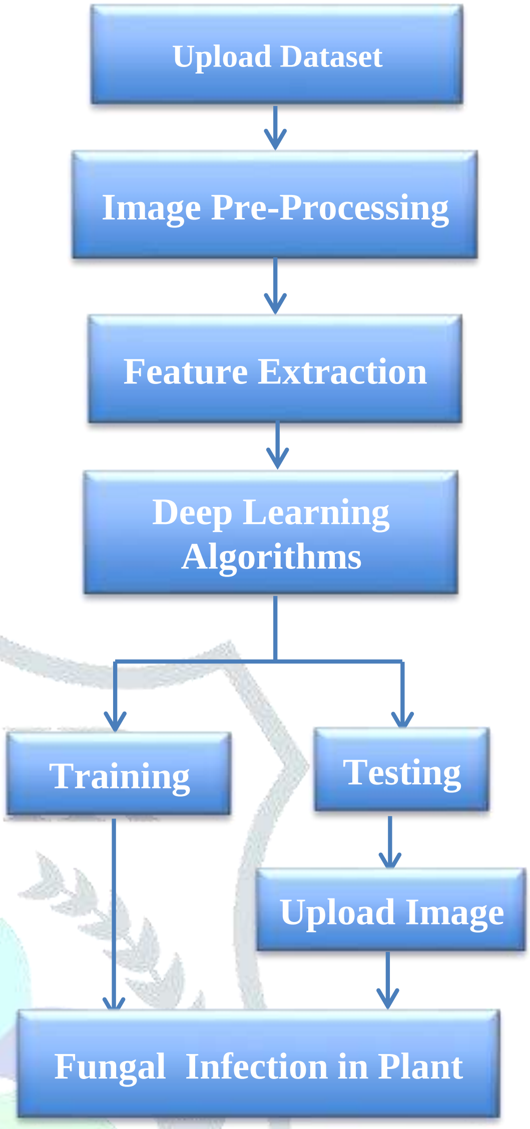


**Fig 1: Proposed System Architecture**

**1) Upload Dataset**

Here we use the pre prepared plant village dataset which is taken from kaggle contains the information about three different types data like color, gray scale and segmented images The dataset contains around 70,295 botanical leaf photographs of the following fruits and vegetables like Tomato, Strawberry, Squash, Potato, Soybean, Raspberry, Corn, Grapes, Orange, Peach, Pepper bells, Cherry, Blueberry and Apple. In the total dataset 70% is used for training and 30% is used for testing.

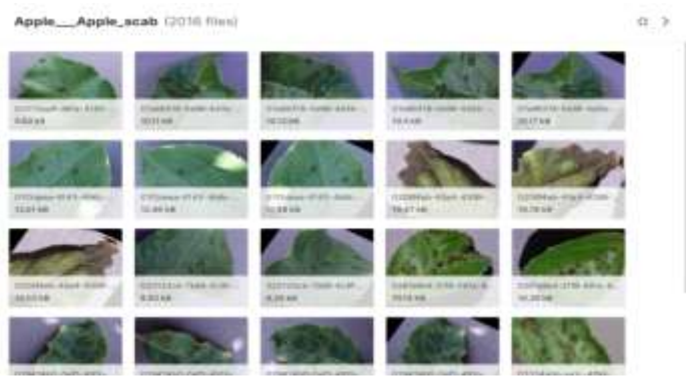


**Figure 2: Plant Village Dataset**

**1. Data preprocessing :**

The process of converting unprocessed image data into a format that is appropriate for analysis is known as image preprocessing. Resizing and reshaping the images into appropriate format to train our model. In this we use different methods like resize, normalization, noise removal, data augmentation and edge detection etc.

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**2. Feature Extraction:**

Feature extraction in images refers to identifying and isolating important characteristics or patterns from visual data that can be used for further analysis, such as in machine learning, computer vision, or image processing. These features could be edges, textures, shapes, colors, or specific objects, depending on the application.

**3. Training**

A. Model training with classifier
B. Accuracy
C. Save model

In this module classification will done and accuracy of the model will be explained.

**4. Results Prediction**

A. Input test data
B. Load model
C. View Result

## IV. DEEP LEARNING ALGORITHMS

**Convolutional Neural Network:**

**Step1: convolutional operation**

It is a type of deep learning model commonly used in the field of computer vision, though it has applications in other domains as well. CNNs are particularly effective for analyzing visual data because of their ability to automatically and adaptively learn spatial hierarchies of features from input images.

**Step 2: Pooling Layer**

The feature maps' spatial dimensions are decreased via pooling layers, or down sampling. The most popular kind, known as max pooling, uses a tiny window of the feature map to extract the maximum value.Pooling keeps the most crucial data while preventing overfitting and lowering computational complexity.

**Step 3: Flattening**

Here, we provide an overview of the flattening process and how to move from pooling to flattened layers in convolutional neural networks.

**Step 4: Full Connection**

The high-level feature maps are first pooled and convolutional via multiple layers until they become a one-dimensional vector. This vector is then fed into one or more fully linked (dense) layers. The conventional feedforward neural network, in which each neuron is connected to every other neuron in the layer before it, is comparable to these layers.Usually, the last completely linked layer produces a probability distribution over the class labels.

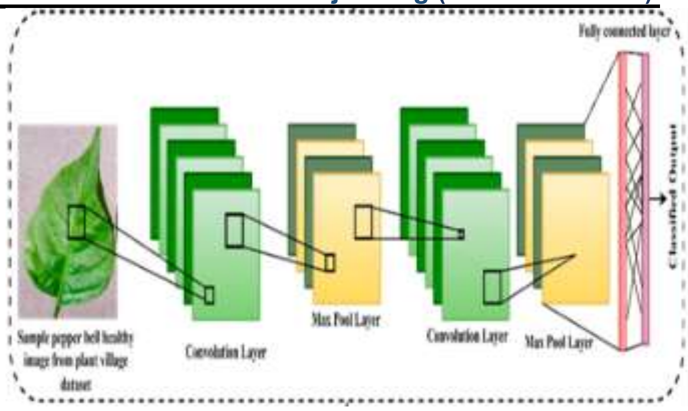


**Fig 3: CNN Architecture**

**Mobile Net:**

Mobile Net is a family of deep learning models designed for efficient image classification and object detection. At the core of MobileNet's design is the use of depth wise separable convolutions, a key innovation that significantly reduces the number of parameters and computational cost compared to traditional convolutional layers. Mobile Net utilizes batch normalization and ReLU6 activation functions to stabilize training and improve generalization.

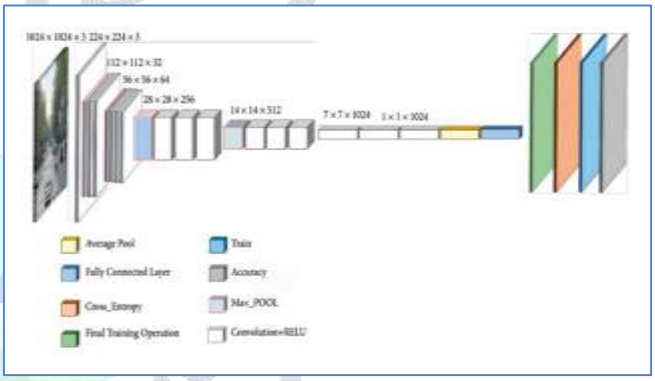

**Fig 4: Mobile Net Architecture**

## V. RESULTS


**Fig 3: Upload Image**

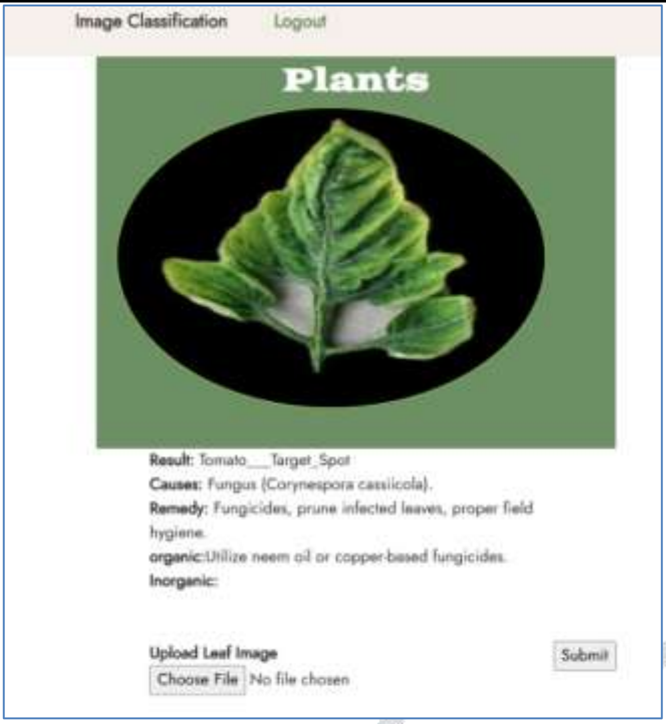


Fig 4: Tomato Target Spot Infection


Fig 5: Apple Scab Infection


Fig 6: Corn Common Rust Infection

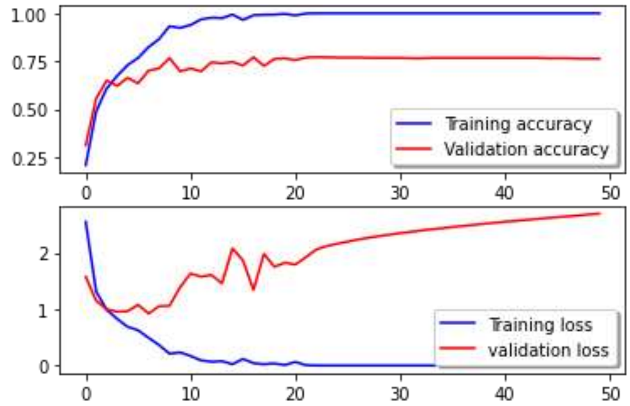


Fig 7: Training Accuracy using CNN

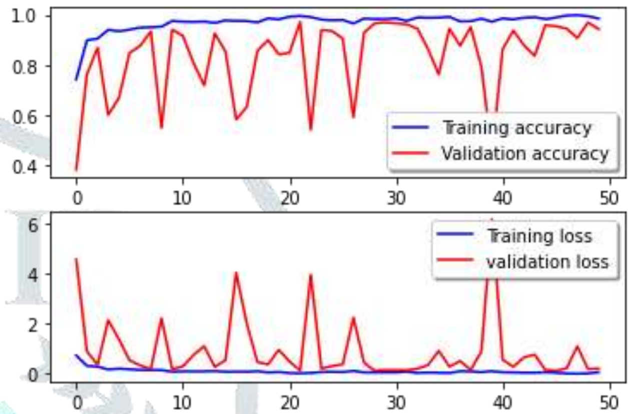


Fig 8: Training Accuracy using Mobile Net

## VI. CONCLUSION

In conclusion, the application of deep learning in detecting fungal infection in plants paper we build a model that which can predict the plant fungal infection by applying CNN and MobileNet a for the process of training image dataset. Once after training, we have checked the classified results for the provided input image and then the precautions are provided for the infected leaf. Here we are getting more accuracy 96% with CNN compared to Mobile Net so for classification we are using CNN.

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