Image Based Deep Learning Approach for Plant Disease Detection

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ABSTRACT
Agricultural productivity and quality are seriously influenced by plant illnesses, causes endangering global food security. Consequently, early detection and treatment of these diseases should be embraced to mitigate losses while enabling sustainable agriculture. Over the years there has been a great progress due to emergence of deep learning techniques for optimizing the image-based process of detecting plant diseases. The objective of this research is to diagnose agricultural diseases accurately and effectively based on an image-based deep learning approach for plant disease identification. As a suggestion, the method involves using convolutional neural networks (CNNs) to identify appropriate features in plant images that can subsequently be used to determine whether they are healthy or sick. A set of images which include both healthy and diseased plants is employed during training and evaluation processes. The model architecture consists of multiple convolutional and pooling layers to extract relevant features from input images. To prevent overfitting, dropout layers are added, and the model is trained with a small learning rate of 0.0001. The CNN is trained on a dataset of 70,295 training images and validated on 17,572 validation images belonging to 38 different classes of plant diseases. The model achieves a high training accuracy of 97.82% and a validation accuracy of 94.59%. Additionally, the evaluation of a model's performance involves several metrics, including precision, recall, and the F1-score showing promising results for practical application in agriculture.

Keywords: Plant Disease Diagnosis, Deep Learning, CNN, Food safety.

1. INTRODUCTION

Agriculture, one of the oldest works, has practiced since ancient times. Plants are an important part of our life. In India, 51% of the population depends on agriculture sector either directly or through indirect means. Yet, due to several abnormal developmental activities like environmental factors, pollution, etc., that causes different kind of diseases which can affect the normal growth of plants. Similar to mammals, plants are also suffering from varieties of abnormal diseases. The biological factors that cause the plant diseases are known as pathogens.

1.1. Pathogens in Plants

Plant disease causing microorganisms are called pathogens; these may include bacteria, fungi, viruses, nematodes and other microorganisms. Pathogens attack various parts of the plant including leaves, stems, roots and fruits thereby manifesting themselves in symptoms such as leaf spots, wilting, rotting and stunting. Every kind of pathogen has its specific characteristics and ways to invade. Like for instance fungal pathogens often produce spores which can be spread by wind water or insects while bacterial organisms can penetrate into plants through wounds or natural openings. Viruses on the other hand are often transmitted by insect vectors or through infected plant materials. When a pathogen enters the plant, it can multiply and disseminate resulting in disease development. Diseases of plants triggered by pathogens are known to have great economic and environmental impacts that reduce crop yield and quality. Some of pathogens in plants given below:

- **Virus**: A virus is a tiny particle microorganism that acts as a bridge between both living and nonliving entities. It remains inactive outside a host but can replicate only when inside a living organism.
- **Bacteria:**Bacteria are microscopic organisms classified as prokaryotes. They are ubiquitous and can cause diseases, spreading widely among plants. Bacteria were among the first pathogens to appear on earth.
- **Fungi:**Fungi are eukaryotic organisms that include microorganisms such as yeast and molds. Fungi play a crucial role in the decomposition of dead plants; they break down organic matter, like leaves and wood, into nutrients that can be used by plants and other organisms.
- **Nematodes:**Nematodes are also known as roundworms which is a diverse group of organisms that belong to the phylum Nematoda. Nematodes are tiny worms that can be both good and bad for farmers. Some nematodes are helpful because they eat bacteria and other tiny organisms, which can be good for the soil. However, there are also nematodes that are harmful. These nematodes attack plants and can damage crops by eating their roots. This can lead to lower crop yields and sometimes even kill the plants.

A plant disease occurs when a plant experiences abnormal growth and development due to disturbance in its normal processes. Plant diseases can be caused by a variety of factors, which are generally categorized into biotic (living) and abiotic (non-living) causes. Various factors of plant diseases, bacterial diseases and affected plants, fungi diseases and affected plants, virul diseases and affected plants, and some nematode diseases and affected plants have been shown in table 1, table 2, table 3, table 4 and table 5 respectively.

Table 1. actors of Plant diseases

Biotic Causes	Abiotic Causes
Fungi	Nutrient Deficiencies
Insects and Pests	Pesticides Exposure
Virus	Environmental factors
Bacteria	Improper Cultural Practices
Protozoa	Soil pH and Salinity
Phytoplasmas and Spiroplasmas	Chemical Damages

1.2. Several names of Plant Disease

Common plant diseases can vary based on the type of plant and the region, but here are some general names and descriptions of common plant diseases:

Table 2. Some common bacterial diseases that affect plants

BacterialDiseases	Plants
Crown Gall	Herbaceous plants
Bacterial Spot	Peppers and Tomato
Soft Rot	potatoes, carrots
Bacterial Leaf Streak	wheat and barley

Table 3. Fungi diseases and affected plants

Fungal Diseases	Plants
Late Blight	Potatoes and tomatoes
Downy Mildew	Grapes
Early Blight	Tomatoes and potatoes
Anthracnose	Beans, cucurbits
Rust	Wheat, corn
Fusarium Wilt	Cucurbits, bananas

Table 4. Viral diseases and affectd plants

Viral Diseases	Plants
Tobacco Mosaic Virus (TMV)	Tomatoes, Peppers
Cucumber Mosaic Virus (CMV)	Melons, Squashes
Potato Virus Y (PVY)	Potatoes, Tomatoes

Cauliflower Mosaic Virus	Cauliflower,Cabbage
Tomato Yellow Leaf Curl Virus	Tomatoes

Table 5. Common nematode diseases

Disease	**Affected Plant**
Cyst Nematodes	Potatoes and soybeans
Root-Knot Nematodes	Tomatoes and Peppers
Root-Lesion Nematodes	Potatoes and Bananas

1.3. Innovative Solutions for Agricultural Challenges

- Human survival is strictly linked to the existence of plants and animals. While they do not depend on us, we depend on them for our survival. However, their productivity has been strongly affected by ecological factors, leading to the emergence of unfamiliar and harmful diseases. It is important to identify, diagnose, and treat these kinds of diseases using our newly developed system.
- Plant Disease Detection and Recognition involves analyzing images of plant diseases to identify and highlight disease based on pattern, texture, and other characteristics.
- Farmers often misuse pesticides or insecticides, which can further harm their crops, Due to a lack of knowledge about the types of diseases affecting crops. Additionally, farmers may struggle to access specialists due to long distances and communication or transportation costs.
- Plant diseases have a devastating impact, significantly reducing the quality as well as quantity of agricultural products. This has particularly negative effects on countries that depend heavily on agriculture for their economy. Therefore, studying and detecting plant diseases is essential, as it can help to monitor large areas of crops and Identify disease symptoms on plant leaves as soon as they appear.
- Farmers often struggle to efficiently understand their crops' health using traditional methods. Accurately detecting crop health, soil quality, and pest infestations can be challenging without advanced technology.
- To create my plant disease detection model using Keras and Tensor Flow, I began with gathering a dataset of healthy and diseased plant leaf images. I preprocessed these images by resizing and normalizing them, and then split the dataset into training, validation and test sets. I imported necessary libraries like Tensor Flow, keras, and matplotlib. I used "Image Data Generator" to augment the training images, enhancing the model's robustness. I built a Sequential model, adding convolutional, max pooling, flattening, dense, and dropout layers. I compiled the model using an optimizer, loss function, and metrics. I trained the model using the training and validation sets and evaluated its performance on the test set. Finally, I visualized the training process by plotting accuracy and loss over epochs to assess the model's performance.

1.4. Problem Statement

- Agriculture is essential for sustaining the food chain for the growing global population. On an average, annual global food chain supply losses due to plant diseases is up to 40%.
- In countries like India, farmers contribute 80% to agricultural production. For them, crop losses have severe consequences overall.
- Sometimes, farmers can suffer nearly complete crop losses due to plant diseases. This makes the significant threat and hence crop diseases pose to food security worldwide.
- The integration of image processing technology within agricultural sector represents a significant step towards enhancing efficiency and sustainability. By advance automated vision systems, farmers can now streamline their operations and increase their productivity while reducing costs and environmental impact.
- This project employs image content-based characterization and a supervised classifier, such as a neural network.

The identification and diagnosis of plant leaf diseases can be approached as a methodology. Digital image processing serves as a tactic employed in this process. Pre-processing of image is done to obtain clear, noise-free improved leaf images, which is utilized for disease detection and analysis. Various techniques are employed in image pre-processing. Typically, color and texture features of plant leaf images are important for disease detection and analysis.

2. LITERATURE REVIEW

Park et al. [1]proposed a deep learning-based technique for disease detection and prediction utilizing image data. It dynamically analyses disease images, and the analysis results are promptly delivered to the farmer who has to make the decision and the feedback from the farmer included in the model.Elangovan et al. [2], Vibhute et al. [3] and Militanteet al. [4] discussed several approaches for segmenting the diseased section of the plant as well as classification techniques for extracting the characteristics of infected leaves and classifying plant diseases using SVM classifier.Chen et al. [5] proposed a method for identification and classification of plant leaf diseases. The feature extraction study is carried out using the image processing techniques then the GMDH-Logistic model is fed with the chosen characteristics. The results show that the approach performed well and can determine if a plant is infected or not. Atila et al. [6], Mohanty et al. [7], Durmus et al. [13] and LeChun et al. [10] proposed deep learning architecture for plant leaf disease detection and classification and the performance of the model was compared and significant improvement has been achieved with other state-of-the-art deep learning models. Benuwa et al. [8] and Lee et al. [11], Ferentinos et al. [12] discussed in detail about the importance of the deep learning in detection and identification of the leaf features and how actually the feature extraction is performed. Paul et al. [9] gives an overview of machine learning and computer vision techniques which are inherently associated with plant disease detection. The role of different seeds, crops and fruits with the country are also considered in the study. Tooa et al. [14] explains about Convolution neural networks which has shown to be useful for accurately and fairly identifying the microorganisms that cause plant diseases. The rapid and precise image detection and display capabilities of advanced deep learning have been shown as a significant revolution in this sector. The Inception V4, VGG 16 OverNet with DenseNets and 50, 101, and 152 layers with 121 layers are the structures that were examined. The investigation made use of 38 distinct categories containing images of the healthy and unhealthy leaves of 14 plants from the plant Hamlet. Of the 38 different varieties of plants—both healthy and sick—that were photographed for the purpose of evaluating the image, 14 came from a plant hamlet. We hope for a precise and efficient outcome that would expedite the elimination of the illness for a stronger existence for the plants. In this way, food defense may be achieved and the load of food waste from the entire country can be reduced. It has been observed that, despite the growing quantity of epics, DenseNets has performed adequately in its appropriate evaluation. Furthermore, it requires less time and produces outcomes quickly. The fact that the outcome is 99.75% factual has been found, demonstrating its effectiveness. It was important to use Keras with Theano support to evaluate the architecture's training.

Mishraa et al. [15] introduce a real-time method based on deep convolution neural network. The performance of a deep neural network can be enhanced by appropriately adjusting the hyper-parameters and pulling combinations on a GPU-equipped device. This device's parameters are tailored to provide the desired outcome in the allotted time. Using an Intel Movidius Neural Compute stick with specialized CNN hardware blocks, the pre-trained Deep CNN model was successfully deployed on a Raspberry Pi 3, enhancing its functionality. The demonstration of the maize leaf disease has been accomplished with an accuracy of 88.46%. It displays how compatible this system is. For convenience, this model can also be utilized with smart devices like as drones and Raspberry Pi. Since corn is an indigenous crop to the Indian population, the disease that is attacking them has raised concerns because it might have a significant impact on the country's economy and jeopardize food security. Effective application of technology can revolutionize the correct elimination of such diseases, enabling timely treatment and the achievement of food security.

Konstantinos et al. [16] applied convolutional neural network models in this paper and deep learning techniques which can be utilized to compare photos of healthy and sick leaves in order to detect and diagnose plant diseases. An experiment comprising 25 distinct plant combinations with disease and healthy plants was carried out using 87,848 photos. Several tests were conducted, the most successful of which achieved accuracy of 99.535 in identifying any plant disease. We can conclude that this experiment demonstrated the model's notable performance in identifying plant diseases early on. It will undoubtedly be useful as a pre-harvest warning system in the agricultural sector, enabling farmers to grow crops with good yields.

Chena et al. [17] explain that plant diseases can therefore be identified and detected using a variety of techniques, deep learning being one of them. Agriculture contributes significantly to India's GDP and ensures food security. However, a number of factors, including population growth, climate change, and global warming, have led to plant diseases that have affected not only the quantity but also the quality of agricultural output.

Le et al. [18] proposes the k-FLBPCM approach, which combines contour masks with LBP feature extraction to improve plant classification accuracy while minimizing noise. The findings indicate that variables number, such as complexity of outside plant morphological variety, can reduce the accuracy of weed identification. On the basis of experimental findings, the k-FLBPCM technique performed best in identifying plants with similar morphology, with an accuracy of 98.63%. This technique is especially

helpful for differentiating between two classes that share a great deal of morphological similarity while allowing for some morphological variation within each class. Additionally, the results demonstrate that the suggested approach's execution time is quicker than combined LBP approach. Consequently, suggested approach aids in the better classification of plants that share morphological characteristics. Moreover, this method's quick processing speed improves its real-time plant detecting capabilities.
Ahmadet al. [19] suggested a self-operating method for image-based characterization of plant disease using Support Vector Machine (SVM) as a classifier and Directional Local Quinary Patterns (DLQP) as feature descriptors. The suggested system, which is DLQP based, is intended primarily for agricultural use. For experimentation, six tomato leaf illnesses, three potato leaf diseases, and three apple leaf diseases are collected. We conducted a classification approach for each condition and evaluated the distinct performance of, LTP, LBP and DLQP as feature descriptors. It is discovered that the suggested DLQP as texture feature description enhances plant disease phenotyping performance. With DLQP and the Medium Gaussian kernel for SVM, the highest detection efficiencies of 97.8% for apples, 95.6% for tomatoes, and 96.2% for potatoes are attained. Furthermore, A thorough comparison reveals that the suggested approach outperforms the current approaches by a large margin. Although the suggested method for plant disease phenotyping yields encouraging results, it could be improved by combining other shape and color-based feature descriptors with DLQP.

3. PROPOSED METHODOLOGY

The proposed work aims to develop an efficient and accurate deep learning-based model for plant disease detection using image analysis techniques. The research methodology will focus on classifying images of plant leaves into healthy or diseased categories to enable early detection and management of plant diseases.

3.1. Tools and Techniques

Following are the tools and techniques used in this work:

3.1.1 CNN(ConvolutionalNeuralNetwork)

CNNs are a type of neural network that are frequently used for image recognition analysis. It has been demonstrated to be more effective than the conventional approach. Through optimized learning and algorithm, it demonstrates a basic pattern.
Three main types of Convolutional Neural Network (CNN) architectures:

- Convolution Layer: It is the most important part of CNN is the convolutional layer that uses the several convolution kernel sizes to import the unique properties of the given image. After applying the convolutional layers multiple times, a set of feature maps of the input images can be retrieved.
- Poling Layer:After convolution layer, the pooling layer is positioned to compile the feature map's statistics. The basic method of pooling entails reducing the number of trainable parameters by down sampling the feature map.

Full Connection Layer:Last final few fully connected layers of a CNN. Every neuron in the previous layer receives input from every other neuron. The receptive field is the entire layer above. In a convolutional layer, the receptive area is less than the entire preceding layer.

3.1.2 Deep Learning

A form of machine learning known as deep learning uses an artificial neural network at a hierarchical level to carry out the machine learning process. The structure of an artificial neural network is inspired by the neural brain. In contrast, conventional programming builds analyses using data in a linear fashion. The deep learning system's hierarchical function enables non-linear data processing on a machine.

3.1.3 Machine Learning

A subset of artificial intelligence, machine learning (ML) focuses primarily on artificial intelligence (AI) through experience and forecasting based on that experience. Machine learning (ML) is the scientific study of statistical models and algorithms that enable computer systems to carry out certain tasks without the need for explicit instructions, instead relying on patterns and conclusions. It is regarded as a subset of artificial intelligence. A mathematical model based on samples is produced by ML algorithms. recognized as training data to make judgments or predictions without the need for special programming to complete the task. An informative collection is used to prepare an AI calculation in order to create a model. To create a model that accurately predicts an outcome, machine learning (ML) begins with reading and analyzing training data in order to identify relevant patterns and insights. The test information set is then used to evaluate the model's efficiency. This process is continued until the machine, acting independently of humans, learns and maps the input to the appropriate output.

3.1.4 Neural Network

Neural networks are frequently compared to computers that are intended to simulate the way the brain operates on a particular task or function of interest. Neural networks are similar to the brain in that they learn by doing. Knowledge is stored in synaptic weights, which are the intensities of connections between neurons. whose purpose is to switch the network's synaptic weights in an orderly fashion in order to achieve a planned design goal.

3.1.5 Transfer Learning

Transfer learning is a machine learning technique where CNNs trained for one task is reused as the starting point for a model on another task. This is done by using a pre-trained network on large labeled datasets, such as public image datasets, to initialize the weights rather than starting the training from scratch and randomly. In this work, we examine the use of pertained models that were trained on the large-scale typical dataset ImageNet, and then apply them to the particular job that was trained on the goal dataset.

3.1.6 Dataset

Plant leaf images were used to test and train deep learning models for the purpose of classifying and identifying disease inimage sets. This study utilizes publicly available and freely licensed datasets from the Plant Disease Dataset. 87,867 images in the Plant Disease Dataset show 26 illnesses affecting 14 different crop plants. The original photographs are colored and come in different sizes. For the VGG net, ResNet, and DenseNets designs, the photos are first downsized to 128 by 128 pixels. In contrast, the photos are downsized to 128 by 128 pixels for Inception V4 architecture. All pixel values are divided by 255 to complete the normalization of knowledge and make them compatible with the initial values of the network. In addition, the target variable or categorical variable is finished being encoded once in order to be used in the models under study. First, the data is divided into two groups. The test data comes after the training data, with a percentage ratio of 20% and 80%, respectively. The models are predicted and evaluated using the tested dataset. The training data is split into training and validation data at ratios of 80% and 20%, respectively, to assess if the model is overfitting.

Key Components of the CNN Model Architecture

- The convolution neural network required a fixed-size RGB image with dimensions of 128 × 128 as input. Its only preprocessing involves deducting from each pixel this mean RGB values that are calculated from the training dataset.
- After that, the picture passes through a series of convolutional layers that contain filters with a 3 × 3 receptive field, the smallest size possible for capturing the concepts of left/right, center and up/down portion.

Summary of the proposed model are as follows:

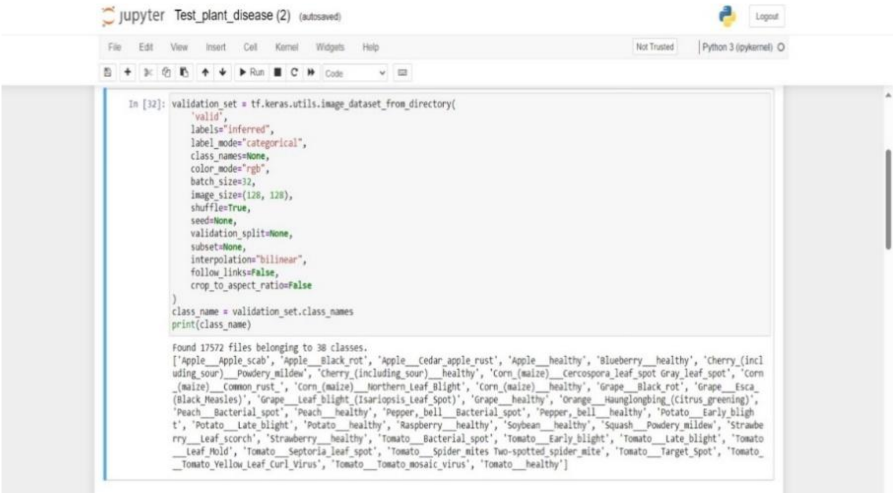
- Inputto modelisfixedto128×128RGBimage
- Conv2D Layers: 10 layers with 32, 32, 64, 64, 128, 128, 256, 256, 512 and 512 filters respectively, each followed by ReLU activation an 'Same' padding.
- MaxPooling2D Layers: 5 layers with a pool size of 2x2 and stride of 2.
- Dropout: Added with a rate of 0.25 after the fifth MaxPooling2D layer. Add another Dropout layer after dense layer with a dropout rate of 0.4 for regularization.
- Flatten: Flattens the output from the convolutional layers.
- Dense Layers: Two dense layers with 1500 units and ReLU activation, and 38 units with softmax activation for classification.
- Adam optimizer is used with a learning rate of 0.0001 is used to minimize the loss.
- Categorical cross-entropy is the loss function used for multi-class classification.
- Model performance is evaluated based on accuracy.
- The model is trained using the training set and validated using the validation set for 10 epochs.
- The fit method returns a history object containing training metrics such as loss and accuracy for each epoch.

3.2. Working of the proposed model

The proposed work aims to develop an efficient and accurate deep learning-based model for plant disease detection using image analysis techniques. The research methodology will focus on classifying images of plant leaves into healthy or diseased categories to enable early detection and management of plant diseases.

3.2.1. Processing of Image Data Set

Offline augmentation is used to recreate this dataset from the original dataset. "https://www.kaggle.com/datasets/vipoooool/new-plant-diseases-dataset" is the link to the original dataset. This dataset is divided into 38 classes which includes over 87,867 rgb images of both healthy and diseases crop leaf. The entire dataset is split up into training and validation sets as 80/20 ratio while maintaining the structure of directory as shown in fig 1. For prediction purposes, a new directory with 33 test photos is later established.



```
In [32]: validation_set = tf.keras.utils.image_dataset_from_directory(
             'valid',
             labels="inferred",
             label_mode="categorical",
             class_names=None,
             color_mode="rgb",
             batch_size=32,
             image_size=(128, 128),
             shuffle=True,
             seed=None,
             validation_split=None,
             subset=None,
             interpolation="bilinear",
             follow_links=False,
             crop_to_aspect_ratio=False
         )
         class_name = validation_set.class_names
         print(class_name)

Found 17572 files belonging to 38 classes.
['Apple___Apple_scab', 'Apple___Black_rot', 'Apple___Cedar_apple_rust', 'Apple___healthy', 'Blueberry___healthy', 'Cherry_(including_sour)___Powdery_mildew', 'Cherry_(including_sour)___healthy', 'Corn_(maize)___Cercospora_leaf_spot Gray_leaf_spot', 'Corn_(maize)___Common_rust_', 'Corn_(maize)___Northern_Leaf_Blight', 'Corn_(maize)___healthy', 'Grape___Black_rot', 'Grape___Esca_(Black_Measles)', 'Grape___Leaf_blight_(Isariopsis_Leaf_Spot)', 'Grape___healthy', 'Orange___Haunglongbing_(Citrus_greening)', 'Peach___Bacterial_spot', 'Peach___healthy', 'Pepper,_bell___Bacterial_spot', 'Pepper,_bell___healthy', 'Potato___Early_blight', 'Potato___Late_blight', 'Potato___healthy', 'Raspberry___healthy', 'Soybean___healthy', 'Squash___Powdery_mildew', 'Strawberry___Leaf_scorch', 'Strawberry___healthy', 'Tomato___Bacterial_spot', 'Tomato___Early_blight', 'Tomato___Late_blight', 'Tomato___Leaf_Mold', 'Tomato___Septoria_leaf_spot', 'Tomato___Spider_mites Two-spotted_spider_mite', 'Tomato___Target_Spot', 'Tomato___Tomato_Yellow_Leaf_Curl_Virus', 'Tomato___Tomato_mosaic_virus', 'Tomato___healthy']
```

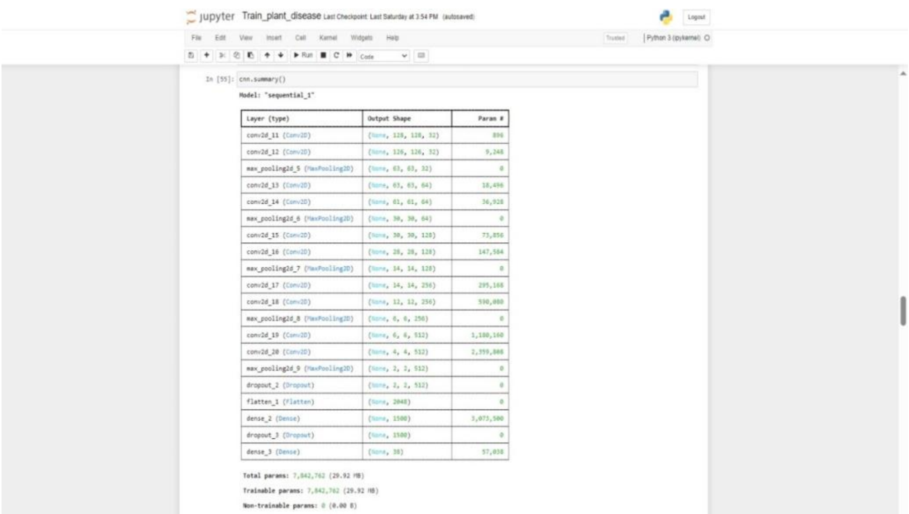
Fig 1. Image dataset used in proposed model

3.2.2. Plant Disease Description

Finding diseases in plants can be a multi-step process involving observation, identification, and sometimes the help of tools or experts. Start by visually inspecting the plants regularly. Look for symptoms such as spots on leaves, wilting, discoloration, abnormal growth, or any other signs of disease. It's important to act quickly if we suspect a plant disease to prevent further spread and damage. Proper identification is key to implementing effective management strategies, which may include cultural practices, chemical treatments, or biological controls.

3.2.3. Overview of a CNN model's architecture

In Figure 2, the model summary function is executed to retrieve the data of all parameters, whether they are trained or non-trained.The "cnn.summary()" function provides a detailed overview of a Convolutional Neural Network (CNN) model's architecture.



```
In [55]: cnn.summary()

Model: "sequential_1"
```

Layer (type)	Output Shape	Param #
conv2d_11 (Conv2D)	(None, 128, 128, 32)	896
conv2d_12 (Conv2D)	(None, 126, 126, 32)	9,248
max_pooling2d_5 (MaxPooling2D)	(None, 63, 63, 32)	0
conv2d_13 (Conv2D)	(None, 63, 63, 64)	18,496
conv2d_14 (Conv2D)	(None, 61, 61, 64)	36,928
max_pooling2d_6 (MaxPooling2D)	(None, 30, 30, 64)	0
conv2d_15 (Conv2D)	(None, 30, 30, 128)	73,856
conv2d_16 (Conv2D)	(None, 28, 28, 128)	147,584
max_pooling2d_7 (MaxPooling2D)	(None, 14, 14, 128)	0
conv2d_17 (Conv2D)	(None, 14, 14, 256)	295,168
conv2d_18 (Conv2D)	(None, 12, 12, 256)	590,080
max_pooling2d_8 (MaxPooling2D)	(None, 6, 6, 256)	0
conv2d_19 (Conv2D)	(None, 6, 6, 512)	1,180,160
conv2d_20 (Conv2D)	(None, 4, 4, 512)	2,359,808
max_pooling2d_9 (MaxPooling2D)	(None, 2, 2, 512)	0
dropout_2 (Dropout)	(None, 2, 2, 512)	0
flatten_1 (Flatten)	(None, 2048)	0
dense_2 (Dense)	(None, 1500)	3,073,500
dropout_3 (Dropout)	(None, 1500)	0
dense_3 (Dense)	(None, 38)	57,038

```
Total params: 7,842,762 (29.92 MB)
Trainable params: 7,842,762 (29.92 MB)
Non-trainable params: 0 (0.00 B)
```

Fig 2. CNN model's architecture

Each row in the summary represents a layer in the model, showing the type of layer, the output shape of the layer's activations, the number of parameters (weights and biases) in the layer, and the connections between layers. The "Total params" row indicates the total number of parameters in the model, while the "Trainable params" row shows the number of parameters that will be updated during training. The "Non-trainable params" row displays the number of parameters that are not trainable, such as those in a Batch Normalization layer. This summary helps in understanding the structure and complexity of the CNN model.

3.2.4. Number of Epoch in model training

One epoch is completed when the entire dataset is passed forward and backward through the neural network orthe neural network has inspected the whole dataset for at least one time. In figure 3, it shows the number of epochs we used. It's important to work with different numbers of epochs and monitor the performance of our model to find the optimal number for our specific dataset and model architecture.

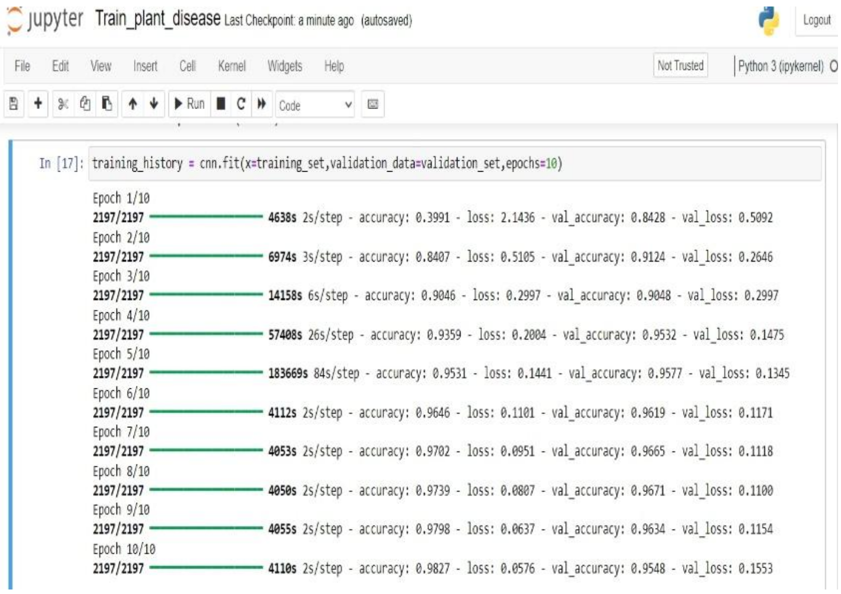


Fig 3. Number of epochs used in model

3.2.5. Web application interface

Figure 4 and 5 shows the web application interface generated by the proposed model. Web application interface for plant disease detection has included a user-friendly dashboard, dataset summaries, and any notifications. Users can upload images of plant parts for analysis, with feedback on the upload progress. After uploading, the system processes the image using a deep learning model and presents the results, including detected diseases, treatment of diseases, and recommended actions.

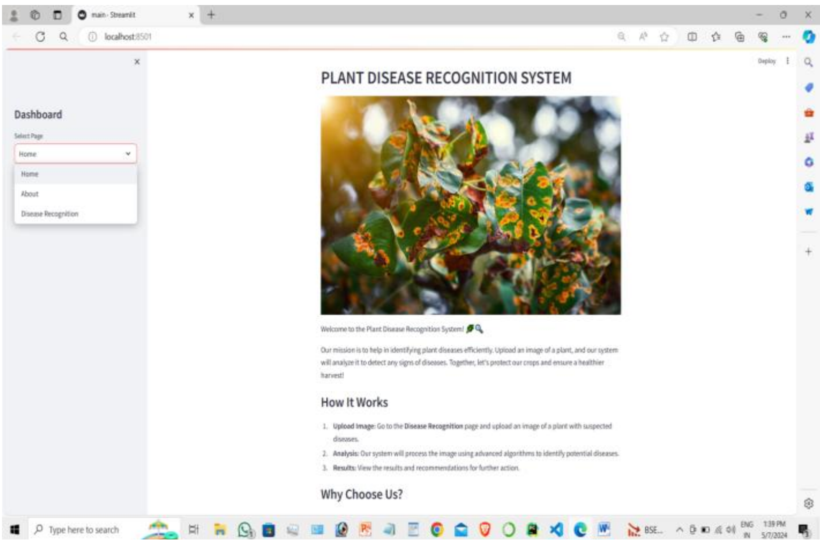


Figure 4. Web application interface: Home Page

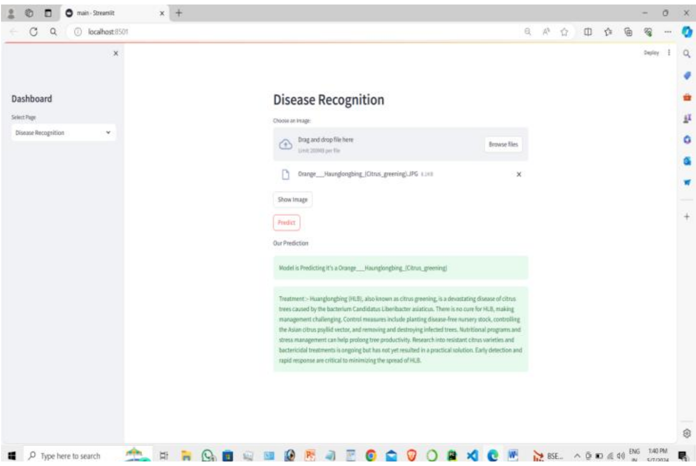


Figure 5. Web application interface: After uploading leaf image with the identified disease

4. RESULT & DISCUSSION

The proposed deep learning model shows an accuracy of 98.68% in classifying plant diseases. The model was trained on a dataset of 87,000 images of diseased and healthy plants, shows a validation accuracy of 95.89%. The high accuracy reflects the effectiveness of deep learning in plant disease detection. The confusion matrix shows that the model had a higher false positive rate for few diseases, indicating areas for improvement. Data augmentation techniques improved the model's performance, particularly for rare diseases with small training samples. Transfer learning using a pre-trained ResNet model significantly reduced training time and improved accuracy. The results show the efficacy of deep learning in plant disease detection and suggest future research directions in improving model interpretability and robustness.

Trainingandvalidationaccuracy have been shown in figure 6.Both training and validation accuracy are expected to increase during training,however, if the training accuracy is improved while the validation accuracy decreases, it may indicate overfitting. In such cases, we may need to use techniques like regularization or early stopping to prevent overfitting.

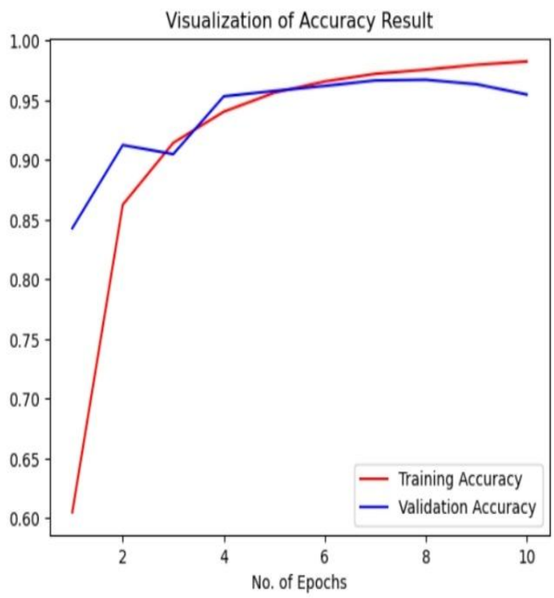


Figure 6. Training and Validation Accuracy

During the training process, both the training loss and the validation loss are typically monitored. If the training loss is decreasing but the validation loss is increasing, it may indicate that the model is over fitting to the training data and not generalizing well. On the other hand, if both the training loss and the validation loss are decreasing, it indicates that the model is learning to make accurate predictions without over fitting. Figure 7 shows the training los and validation loss for the proposed model.

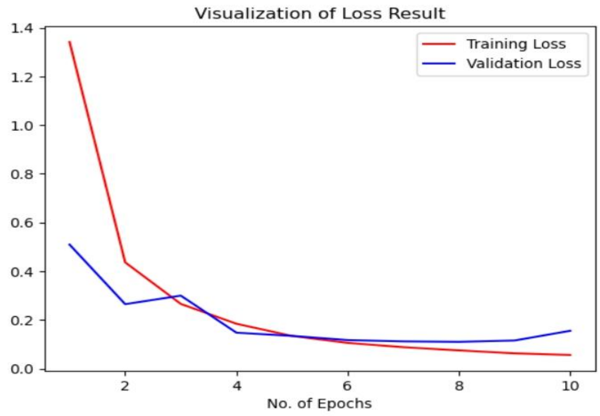


Figure 7. Training andvalidation loss

98.68% of training accuracy has been achieved as shown in figure 8. Model accuracy is a metric that is used to evaluate the machine learning model performance. It is calculated as the ratio of the number of right predictions to total number of model predictions, expressed as a percentage.

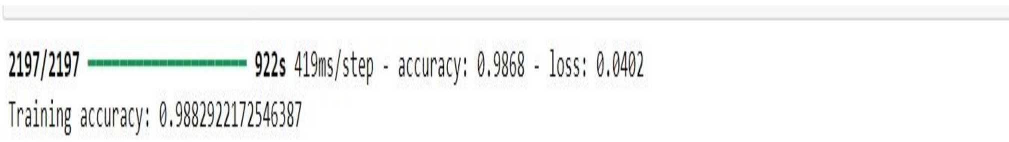

2197/2197 ━━━━━━━━━━━━━━━━━━━━ 922s 419ms/step - accuracy: 0.9868 - loss: 0.0402
Training accuracy: 0.9882922172546387

Figure 8. Model training accuracy

Model validation accuracy of 95.95% has been achieved as shown in figure 9, whichrefers to the accuracy of a machine learning model on a validation dataset. In the context of plant disease detection, this would typically involve splitting the dataset for training, validation, and test sets. The training process involves using the training set to train the model, and then assessing its performance on the validation set. This helps in tuning hyperparameters and avoiding overfitting.

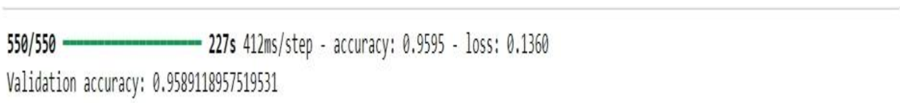

550/550 ━━━━━━━━━━━━━━━━━━━━ 227s 412ms/step - accuracy: 0.9595 - loss: 0.1360
Validation accuracy: 0.9589118957519531

Figure 9. Model validation accuracy

A confusion matrix is a table commonly utilized to illustrate how well a classification model performs on a dataset where the true values are known. It provides a visual representation of an algorithm's performance. In figure 10 confusion matrix has beenshown for evaluating a classification model, the x-axis (horizontal axis) typically represented as predicted classes, while y-axis (vertical axis) represented as actual classes. Each cell in the matrix corresponds to a combination of predicted and actual classes. The diagonal cell from the bottom right and top left represents correct predictions, whereas predicted class matches with the actual class. Off-diagonal cells represented as incorrect predictions, where predicted class does not match actual class.

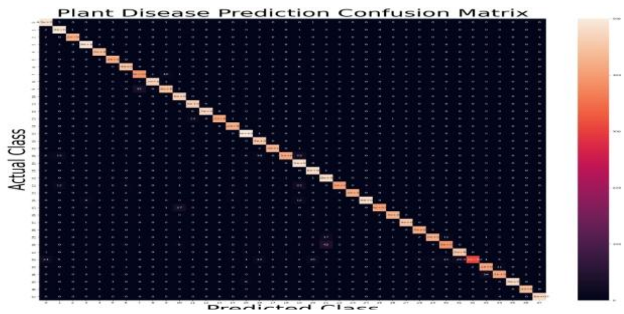


Figure 10. Confusion matrix of the proposed model

Table 6. Evaluation of the model performance

Accuracy	Precision	Recall	F Score
94.59%	95.65%	95.47%	95.42%

The built-in web application makes emailing users convenient and is useful for detecting plant diseases. The proposed model has been evaluated on metrics like accuracy, precision, recall and F Score as shown in table 6. Expanding the program to different crops worldwide will require more photos, training, and instructions for deep learning. To correctly detect a plant disease, image resolution is just as crucial. Interpretations in the farmers' local tongue are crucial for educating them about plant diseases and suitable treatments.

5. CONCLUSION AND FUTURE WORK

Artificial neural networks (ANN) clustering algorithm provide strong support for the image processing-based approach. This method is divided into four basic stages: preprocessing stage, the K-means technique which is used to segment the given images. Some texture features are then retrieved and a pre-trained neural network which is used to test and validate the results. The agricultural industry will undergo a revolution when this futuristic strategy is implemented properly. We will receive a fairly exact figure from some computational work, which will facilitate prompt therapy.

We have the required outcome that will aid in a proper cure after examining soil and land where Bacteria shelter and how to feed the plants. The suggested approach must go through several stages in order to be recognized

- Detect the typeofplants.
- Identifythetypeofdiseasesthatplantissufferingfrom.
- It shows multiplediagnosisoptionsand then suggest some accurate and efficientunderstanding.

Future study should focus on certain areas, such as improving segmentation techniques, choosing better features for extraction, and weeding out classification algorithms.

REFERENCES

[1] H. Park, J.S.Eunand S.H.Kim, Image-based disease diagnosing and predicting of the crops through the deep learning mechanism, In Information and Communication Technology Convergence(ICTC),IEEE 2017 International Conference on,pp.129-131,2017.

[2] K. Elangovan and S. Nalini, Plant disease classification using image segmentation and SVM techniques, International Journal of Computational Intelligence Research, vol.13(7),pp.1821-1828,2017.

[3] A. Vibhute and S. K. Bodhe, Applications of Image Processing in Agriculture: A Survey, International Journal of Computer Applications, vol. 52, no. 2, pp. 34-40, 2012.

[4] S. Militante, Fruit Grading of Garcinia Binucao (Batuan) using Image Processing, International Journal of Recent Technology and Engineering (IJRTE), vol. 8 issue 2, pp. 1829- 1832, 2019

[5] Chen J, Yin H, Zhang D (2020) A self-adaptive classification method for plant disease detection using GMDH-Logistic model. Sustain Comput Inform Syst 28:100415.

[6] Atila Ü et al (2021) Plant leaf disease classification using efficientnet deep learning model. Ecol Inform 61:10118

[7] S.P. Mohanty, D.P. Hughes, and M. Salathé Using deep learning for image-based plant disease detection, in Frontiers in plant science 7, p. 1419, 2016.

[8] B. Benuwa, Y. Zhao Zhan, B. Ghansah, D. Wornyo, & F. Banaseka, A Review of Deep Machine Learning, International Journal of Engineering Research in Africa, 24, pp 124-136, 2016, 10.4028/www.scientific.net/JERA.24.124.

[9] Paul A et al (2020) A review on agricultural advancement based on computer vision and machine learning. Emerging technology in modelling and graphics. Springer, New York, pp 567–581.

[10] Y. LeChun, Y. Bengio and G. Hinton, Deep Learning, Nature, vol.521,pp. 436-444, 2015. eprint https://doi.org/10.1038/nature14539

[11] S. H. Lee, C. S. Chan, S. J. Mayo and P. Remagnino; How deep learning extracts and learns leaf features for the plant classification, Pattern Recognition, vol. 71, pp. 1-13, 2017.

[12] K.P. Ferentinos, Deep learning models for plant disease detection and diagnosis, Computers and Electronics in Agriculture, vol. 145, pp. 311-318, 2018

[13] H. Durmus, E. O. Gunes¸ and M. Kirci, Disease detection on the leaves of the tomato plants by using deep learning, In Agro-Geoinformatics, IEEE 6th International Conference on, pp. 1-5, 2017.

[14] A comparative study of fine-tuning deep learning models for plant disease identification- Edna

Chebet Tooa, Li Yujiana , Sam Njukia , Liu Yingchun
[15] Mishra, Sumita, Rishabh Sachan, and Diksha Rajpal. "Deep convolutional neural network-based detection system for real-time corn plant disease recognition." Procedia Computer Science 167 (2020): 2003-2010.
[16] Deep learning models for plant disease detection and diagnosis-Konstantinos P. Ferentinos 24
[17] Using deep transfer learning for image-based plant disease identification -Junde Chena, Jinxiu Chena, DefuZhanga, YuandongSunb, Y.A. Nanehkarana.
[18] Le VNT et al (2020) A novel method for detecting morphologically similar crops and weeds based on thecombination of contour masks and filtered Local Binary Pattern operators. GigaScience 9(3)giaa017
[19] Ahmad W, Shah S, Irtaza A (2020) Plants disease phenotyping using quinary patterns as texture descriptor. KSII Trans Internet Inf Syst 14(8):3312–3327.