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# Plantest : Machine Learning based Leaf Disease Detector

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**Abstract— Plant health and food safety greatly depend on the early diagnosis of leaf diseases. Traditionally, the majority of the detection techniques used today rely on professional human observation, which is not only labor-intensive but also quite costly and prone to human mistake. Therefore, in order to diagnose plant leaf diseases from photos, this research suggests a machine learning-based technique that makes use of CNNs. A big dataset comprising several images of leaves in various situations and types is used to train it. Techniques for augmentation including rotation, flip, and zoom have been used to increase generalization capability. The proposed CNN Architecture, with an accuracy of approximately 95%, performs better than traditional image processing methods. Given these results, the exceptional accuracy and robustness of**

**Keywords:** ***image classification, data augmentation, machine learning, deep learning, plant pathology, automated disease diagnosis, precision agriculture, computer vision in agriculture, and plant leaf disease detection.***

## I. INTRODUCTION

Agriculture is the backbone of our country. Agriculture is a predominant industry in our country [1-2]. People might be interested in agriculture in India. It plays a massive role in the Indian economy. About 70% of the rural communities rely on agriculture. 60% of the population has access to work possibilities thanks to the GDP, which receives an overall of 17% of its revenue [3-5]. Therefore, the detection of plant diseases is important in agriculture. The image processing method is a suitable technology that is applied to agriculture. Fungi and other bacterial infections are the main causes of damage to plants [6].

Diseases of crop leaves can differ in size, shape, and color. While some diseases have different colors but the same shape, others may have the same color but different shapes. To prevent crop loss owing to disease transmission or increase, a model that is constructed by capturing sick leaves and identifying disease patterns can be helpful [7]. This method frequently sends the photos to a key crop leaf disease

Recent years have seen an increase in image categorization as a trend among technology developers, thanks in large part to the expansion of data in various sectors of the economy, spanning gaming, automobiles, healthcare, and e-commerce. The most obvious application of this technology is found on Facebook. Facebook can now classify your face into your Facebook album with just a few tagged photographs and a detection rate of up to 98% accuracy. The ability of the technology to classify or recognise images is almost superior to that of people [8][9][10].

It is now unable to characterize plant ailments using the typical human method of visual assessment. Modern computer vision models provide quick, standardized, and precise solutions. classification methods can be provided as attachments while preparations are being made. All you require is a web association and a cell phone with a camera. Naturalist and Plant split two well-known business applications to demonstrate how is it feasible. The two apps are excellent at teaching users new skills and creating logical online social communities. Deep Learning recently produced an outstanding results in a number of domains, counting image identification, speech identification, face recognition, and natural language processing. Convolutional neural network algorithms have shown remarkable results in the problem of recognizing plant diseases, demonstrating highly promising findings. The best approach for Object identification is widely acknowledged to be Convolutional Neural Network. Data Processing is particularly critical to model for exact performance. Many illnesses, whether bacterial or viral, can be difficult in detect since their symptoms frequently overlap [11][12][13].

Support vector machines and other classification algorithms are applied in this step. The input images of the neural network are rescaled to reduce processing time and eliminate underfitting. Through training for a specific number of epochs, the performance indicators are evaluated and compared for the classification model. The outcomes showed that the intended approach offers a high degree of accuracy in identifying plant leaf diseases. It shall not be that difficult to identify various diseases because it shall lead towards early detection of plant diseases, which in turn will halt their spread.

## II. Survey of the Literature

Crop yield is greatly threatened by plant diseases, and the manual observation and detection of these diseases using traditional methods is time-consuming and frequently ineffective. Researchers are able to create automated systems for illness detection and diagnosis thanks to the quick development of machine learning techniques.

This section discusses the latest developments in CNN and deep learning architecture applications for the agricultural industry. Prior to the development of deep learning, several plant diseases may be categorized using processing and machine learning approaches [14].

The majority of these systems typically operate as follows: Using a digital camera, the first digital photos are captured. After that, the images are ready for further steps by using image processing techniques like image improvement, segmentation, transforming and filtering the colour space. The image key details are extracted, and the classifier uses these as input [15][16]. As a result, the type of image affects the total classification accuracy approaches for feature extraction and processing applied. The most recent research, however, demonstrates that networks trained on generic data can achieve cuttingedge performance. CNN, a multi-layer supervised network, can automatically identify traits from datasets.

In recent years, CNN's performance in nearly important classification assignments has been cutting edge. Using the same architecture, it can carry out feature extraction and classification [17][18].

Ms. Deepa, Ms. Rasmi N, and Ms. Chinmai Shetty in another work used machine learning with the detection of plant leaf disease. For the clustering method, the K-means clustering was applied, while the feature extraction was made using the gray cooccurrence matrix (GLCM). The classes were defined with the classifier SVM into four classes: healthy leaves, Anthracnose, Alternaria Alternata, and Bacterial Blight. [19]

Vaishnavi Monigari, G. Khyathi, and T. Prathima are trained the CNN using more than 20,000 pictures of healthy and diseased plant leaves covering 15 categories. The authors used the OpenCV framework for image processing and image augmentation to increase the images in the dataset. The developed model correctly could classify the eight different diseases from the healthy leaves with an accuracy rate of 90%. [20]

Finally, Marwan Adanan Jasim and Jamal Mustafa AL-Tuwaijari presented a work on plant leaf disease detection and classification using image processing and learning approaches applied to potato, tomato, and pepper leaves. Their dataset for which CNN was used for classification included more than 20,000 photos. Three classes for healthy leaves and twelve classes for damaged leaves were presented. The accuracy of the model for the training dataset was 98.29%. and for the testing dataset, it was 98.029%. [21]

Aakanksha Rastogi, Ritika Arora, and Shanu Sharma's "Leaf Disease Detection and Grading using Computer Vision Technology & Fuzzy Logic". The faulty region is segmented by applying K-means clustering, texture features are retrieved with GLCM, and fuzzy logic graded the disease. They used ANNs as classifiers in classifying the severity of the leaf sickness [22].

In "Automated Vision-Based Diagnosis of Banana Bacterial Wilt Disease and Black Sigatoka Disease," Godliver Owomugisha, John A. Quinn, Ernest Mwebaze, and James Lwasa collect and convert RGB, L*a*b, and HSV color histograms. Peak components, five shape parameters, and area under the curve analysis are used to produce the maximum tree for categorization. Different algorithms were employed, such as Naïve Bayes, decision trees, random forests, SV classifiers, closest neighbors, and highly randomized trees. Randomized trees give real-time information, variety in application, and excellent performance in seven classifiers [23].

The study by Uan Tian, Chunjiang Zhao, Shenglian Lu, and Xinyu Guo, "SVM-based Multi Classification Systems for Detection of Grain Leaves Diseases," applied GLCM to extract seven invariant moments as the form parameter after transforming RGB to HIS color space. The authors applied an SVM classifier with MCS [24] in an offline manner to detect the disease in the wheat plants.

The matrix is utilised to extract characteristics as well as various techniques like grayscale, histogram intensity, etc. Artificial neurons are used to categorise illness reproduction from holidays in order to provide the best results for each kind, and to maintain the vector engine operating, maintenance vector networks and tools are utilized. smoothly. On paper, RGB images are changed through colour conversion to become grayscale images. Image

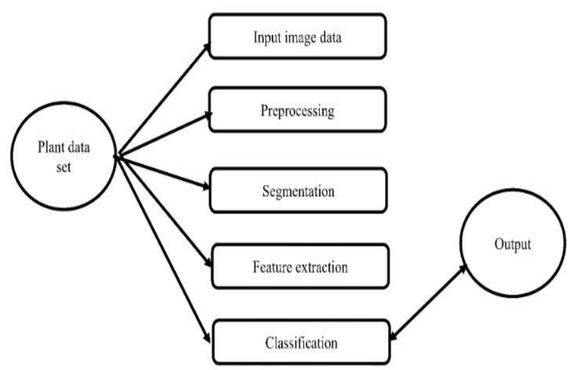


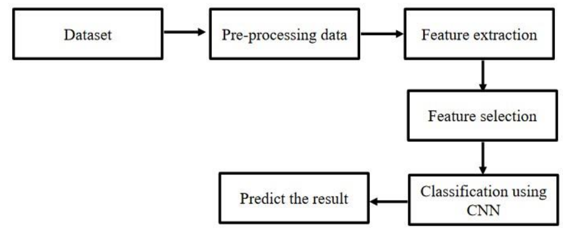

**Figure 2. Use case diagram**

quality is enhanced using a variety of enhancement methods, including contrast adjusting and histogram alignment. Examples of the many classification characteristics used here include B. classification on the reports from SVM, ANN, and FUZZY. Distinct kinds of characteristic values are used while extracting functions, including B. textures, structures, and geometrical elements. Plants that have not been peeled can have illnesses identified using the ANN and FUZZY categories [25][26].

## III. PROPOSED METHODOLOGY

### *A . Proposed System*

Image and video processing are commonly employed in speech processing and natural language processing. Simultaneously, it is artificial deep learning of the application Identification of plant diseases and the range of pests evaluation of plant disease identification, which shows that selection's drawbacks can be avoided, is a focus of research in the area of agricultural plant protection, and it has grown to a disease of the spot is equipped with a more feature extraction of objective makeup plant diseases, and improve the exchange rate.of efficiency and technology of research.The suggested method is depicted in Figure 1.




(fig. no. 1)

#### *1). Diagram of the use case*

As seen in Figure 2.2, a use case diagram is a graphical depiction of the interactions between system components. The intended behaviour and the means for achieving it will be specified in use cases. Once defined, use cases can have both written and visual representations.

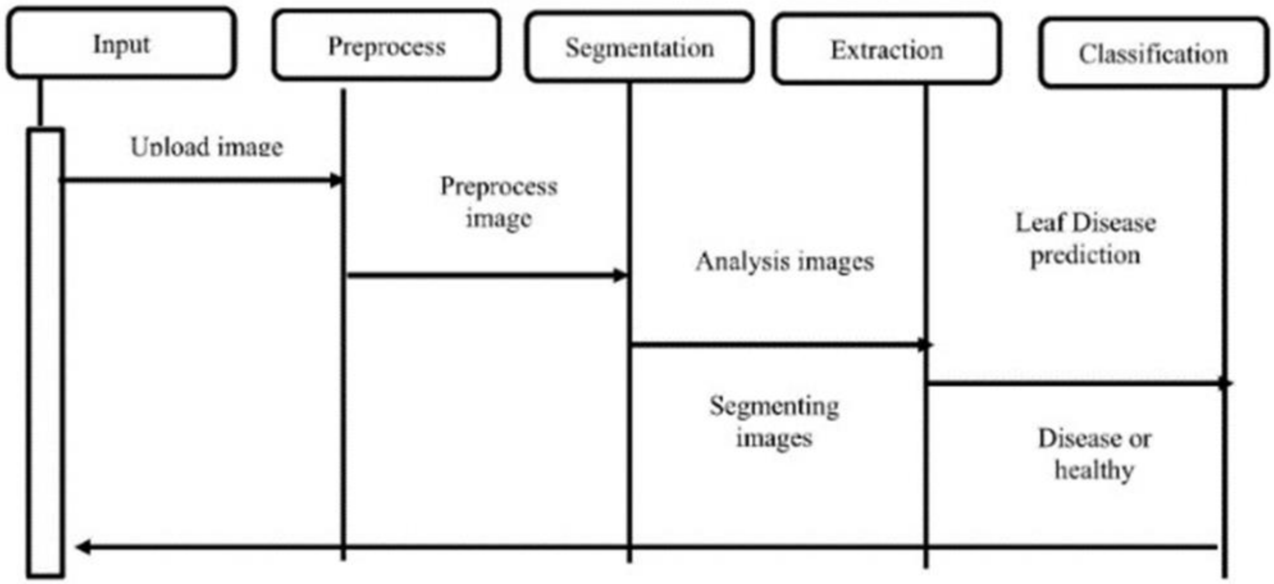



**Figure.3 Sequence diagram**

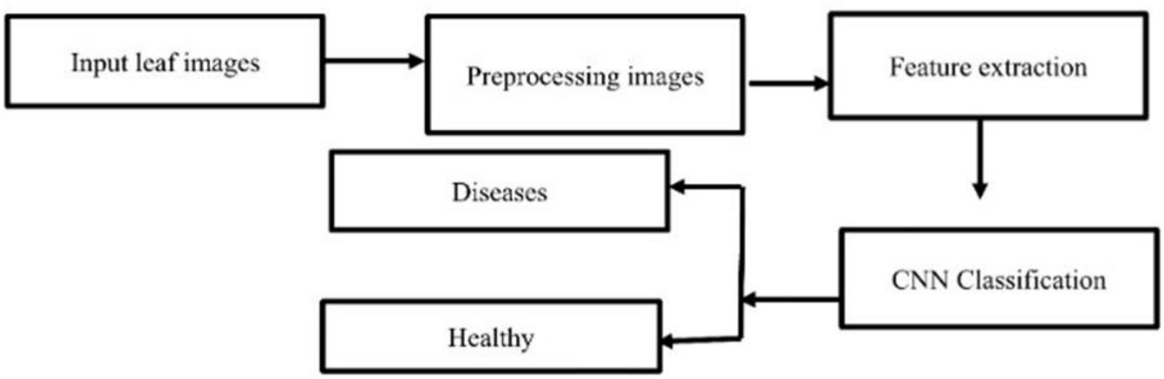



**Figure.4. Activity diagram**

*2) Diagram of the sequence*

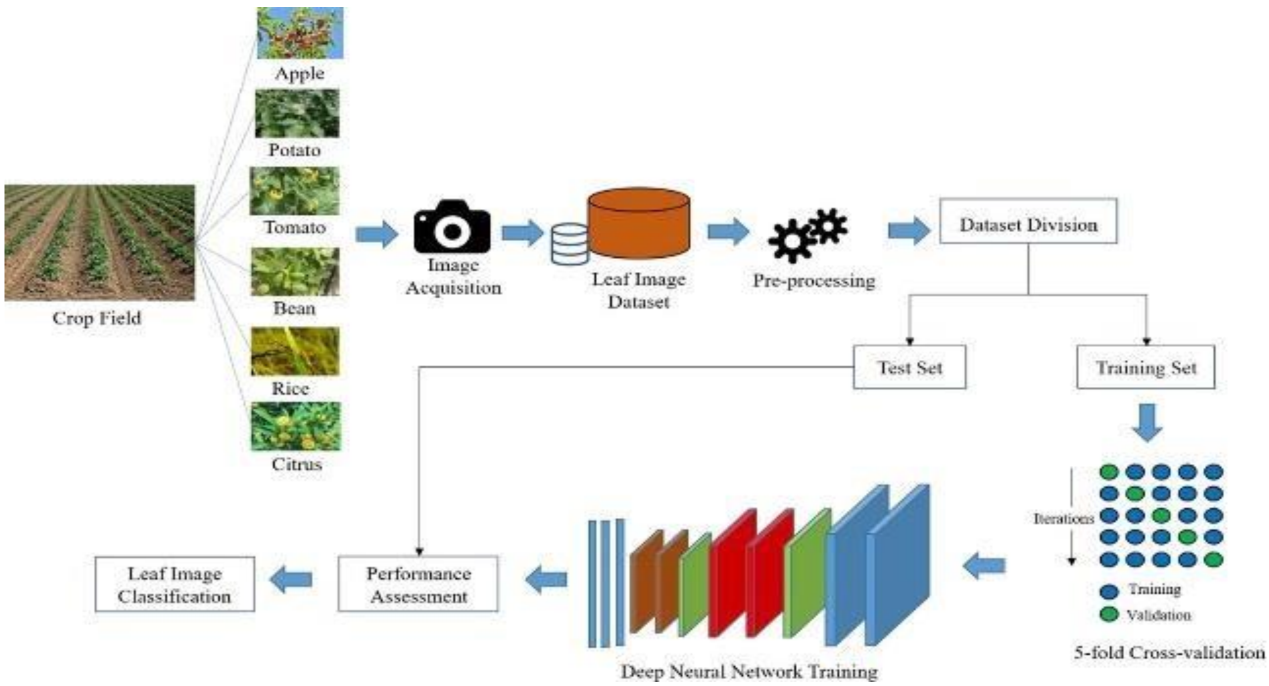
Figure 3. In the sequence diagram shown, objects or processes that interact with one another are represented by paralllel vertical lifelines; the signals passed between them are represented as horizontal arrows in the order that they appear.

*3) Diagram of an activity*

An activity diagram is an important type of UML diagram that will show the dynamic feature of the system. One action leads to the next using an activity diagram, which is essentially a flowchart. System functionality is one method for defining an activity. The control flow guides operation into the next. Figure 4 shows how one activity leads to another. The activity begins with a digital camera image of the leaf and then preprocessed for feature extraction, such as color, shape, texture, and so forth.

*B. Methodology*

Data gathering, data cleaning, architecture design, model training, and evaluation are parts of this proposed machine learning approach for plant leaf disease identification. All steps in developing a machine learning system are addressed here




(fig. no. 5)

model that effectively automates the detection of plant diseases.

*1) Data Collection*

First, this methodology requires the gathering of a suitable dataset of images of plant leaves. In this paper, we used the PlantVillage dataset-a publicly available and popularly used dataset with over 50,000 high-resolution images showing either no signs of disease or displaying symptoms of certain diseases. The dataset contains 38 classes containing healthy leaves and those affected by a number of diseases, including rust, leaf mold, powdery mildew, bacterial spot, early and late blight, and others.

2) Data Pre-processing

Considering the effectiveness of a model, input data quality is very important; thus, several preprocessing steps were performed:

a) Image Resizing: All the images are uniformly resized to 150x150 pixels each. This allows consistency in the dataset and reduces computational complexity with very minimal degradation of the image quality that may affect feature extraction.

b) Normalization: By dividing the pixel values by 255, images were normalized within the interval [0, 1]. This normalizes the data coming into the network at once and eventually increases the speed of convergence during the network training.

Formula for Normalization :

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)}$$

where :

The initial value of the pixel is x.
The normalized value of a pixel is x ′.

The dataset's minimum and maximum pixel values are denoted by the values min(x) and $\max(x)$., respectively.

In the context of images, since pixel values usually range from 0 to 255, normalization is simplified to:

$$x' = \frac{x}{255}$$

c) Data Augmentation: A number of augmentation methods had been employed for a model which can be prevented from overfitting and also could be generalized on new data.

Rotation : Images are rotated randomly to different angles, simulating variations in leaf orientations.Flipping: We apply both horizontal and vertical flipping in order to introduce more variety into the images.

Zooming : We also apply random zooms on the images in order to make the model robust against changes of scale.

Shearing and Shifting: This dataset is further augmented by the application of shear transformation and random shifts.

3) Model Architecture Design

As the task involved identifying plant leaf disease, an architecture known to excel in image classification was adopted, which is the Convolutional Neural Network. This architecture needs to be built with performance and computational efficiency in mind. The CNN model will consist of:

a) Convolutional Layers: A total of three convolutional layers learned hierarchical features in a greedy fashion from the input images: 32, 64, and 128, with increased filter sizes. The filters are set to (3x3), and ReLU has been used to introduce non-linearity.

Formula:

$$y(i, j) = (x * w)(i. j) = \sum \sum x(i - m, j - n). w(m, n)$$

$m \; n$

Where:

- x is the given input image.
- w is the filter (also known as the kernel).
- y(i, j) is the output feature map at position (i, j).
- m, n are filter dimensions.

2) Pooling Layers: Max-pooling layers were introduced after each convolutional layer in order to reduce dimensionality.

Formula:

$$y(i, j) = (x * w)(i. j) = max\{x(i + m, j + n\}$$

Where:

- where the input feature map is referred to as x.
- The pooled feature map is referred to as y(i, j).
- The m, n defines the size of pooling window.

*c) Flattening Layer:* This layer is a flattening layer whose function is that flattens output from final pool layer into single vector so it may be used as input to fully linked layers.

*d) Fully Connected (Dense) Layers:* Two dense layers were used. The first had 512 neurons with ReLU activation and the second was of size equal to the number of classes of the dataset and probability was *assigned to each class with softmax activation.

*e) Dropout Layer:* There was a dropout layer following the flattening layer set at 0.5 dropout rate to prevent overfitting. Dropout layers eliminate during training a random subset of neurons..

*4). Model Training*

The Adam optimizer, whose adaptability in adjusting learning rate makes it one of the most widely used options for deep learning applications, optimizes this. Since there are so many classes involved in the categorization problem at hand, categorical cross-entropy loss function is used. Early stopping was implemented to make the performance robust and prevent it from overfitting. The validation loss is monitored by early halting functions.In the event that the validation loss remains unchanged, as determined by a predetermined number of epochs known as patience, the training process terminates and the model's optimal weights are restores

Formula:

$N \quad M$

$L = -\sum \sum yij \log(\hat{y}ij)$

$i=1\ j=1$

Where:

• N represets the samples in the batch.

• M represents number of classes.

• If class label j correctly classifies sample i, then y_ij is a binary indicator (0 or 1).

• The expected likelihood that sample i belongs to class j is denoted by y<_ij.

*5). Model Assessment*

The model's generalization performance was assessed on a different test dataset after training. The evaluation measures were F1-score, recall, accuracy, and precision. Also, a confusion matrix was created to offer a thorough understanding of how well the model identified various illnesses.

To assess the performance of the model, there are several metrics computed: accuracy, precision, recall, and F1score,

*a) Accuracy*

$$\boldsymbol{Accuracy} = \frac{\boldsymbol{TP + TN}}{\boldsymbol{TP + TN + FP + FN}}$$

where:

- True Positives (TP)
- True Negatives (TN)
- False Positives (FP)

False Negatives (FN)

*b)Precision*

$$\boldsymbol{Precision} = \frac{\boldsymbol{TP}}{\boldsymbol{TP + FP}}$$

*c) Recall (Sensitivity)*

$$\boldsymbol{Precision} = \frac{\boldsymbol{TP}}{\boldsymbol{TP + FN}}$$

*d. F1-Score*

$$\boldsymbol{F1 - score} = \boldsymbol{2} \times \frac{\boldsymbol{Precision} \times \boldsymbol{Recall}}{\boldsymbol{Precision} + \boldsymbol{Recall}}$$

*6) Model Deployment*

After the model has been optimized, it can be deployed. This will entail integrating the model into a web service or mobile application that seeks to solve a practical issue.

*C. ALGORITHMS*

Steps to solve the problem to for detecting the plant leaf disease.

*1) Image Pre-Processing*

- Compile the system's input picture.
- Importing the libraries needed to continue processing the picture. NumPy, Keras, cv2, Tkinter, Pillow, etc.
- Assign the appropriate training and testing routes so that the photos are processed appropriately.
- Define the function "rgb_bgr" and include the appropriate input parameter image in it.
- Using cv2.threshold() in OpenCV for feature extraction.
- Send back the image after processing.

*2) CNN Algorithm*

In projects that employ the CNN architecture, CNN frameworks are crucial. Since each framework was developed uniquely for a specific purpose, at present, we have approach to a wide range of structures that permits us to manufacture tools that can increase knowledge while easing difficult programming issues. Therefore, DL experimental studies can be carried out by researchers using a range of tools and platforms; provides a review of the most popular ones [29][30].

The procedures for teaching a CNN to classify images are as follows:

- Preprocessing and data collection: Gather a dataset of captioned images and scale and standardize the images to prepare the data.
- Model architecture design Select an appropriate CNN architecture for the network; it usually consists of convolutional, pooling, and fully linked layers.
- Compilation: Specifies the metrics, optimizer, and loss function that will be used in training with the model.
- Training Feed in the training data for the CNN and train the model by backpropagation to minimize the loss function.
- Testing: Train the model on a validation set and monitor its performance across time to prevent overfitting.
- Testing: Evaluate the ability of the final model to generalize by using a held-out test set.
- Tuning: Use a smaller learning rate or the same set of data to continue refining for better performance on certain tasks.
- Deployment: Use the trained model in an actual application, such as a mobile application or an online service.IV. RESULT.

Better outcomes than the basic CNNs can be obtained by utilizing customized CNNs, improved deep learning models, and transfer learning models. Traditional ML approaches are not as effective as modified DL techniques. The best accuracy is obtained with the modified CNN, or multi-channel model [27]; this translates to 99.5% accuracy in DL and 99% accuracy in ML approaches using SVM with a linear kernel.

*A. Model Performance Metrics*

1) Accuracy: calculates the proportion of correctly identified photos relative to all images.

$$Accuracy = \frac{Number\ of\ Correct\ Predictions}{Total\ Number\ of\ Predictions}$$

2) Precision: Indicates how many of the predicted disease labels are actually correct. High precision means fewer false positives.

$$Precision = \frac{TP}{TP + FP}$$

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3) Recall (Sensitivity): Measures how many of the actual disease cases are correctly identified by the model. High recall means fewer false negatives.

$$Recall = \frac{TP}{TP + FN}$$

4) F1 Score: Whenever there is an imbalance in classes, a fair assessment can be obtained by the harmonic mean of precision and recall.

$$F1\ score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

| | Predicted: Healthy | Predicted: Disease A | Predicted: Disease B | Predicted: Disease C |
|---|---|---|---|---|
| **Actual: Healthy** | 2500 | 100 | 50 | 30 |
| **Actual: Disease A** | 80 | 2200 | 120 | 50 |
| **Actual: Disease B** | 60 | 100 | 2100 | 70 |
| **Actual: Disease C** | 40 | 90 | 110 | 2300 |

5) Confusion Matrix

A confusion matrix is a table that shows the number of true positives, true negatives, false positives, and false negatives. It provides details on classes being misclassified.

*B. Results Interpretation*

Based on the above metrics, the results can be interpreted as follows:

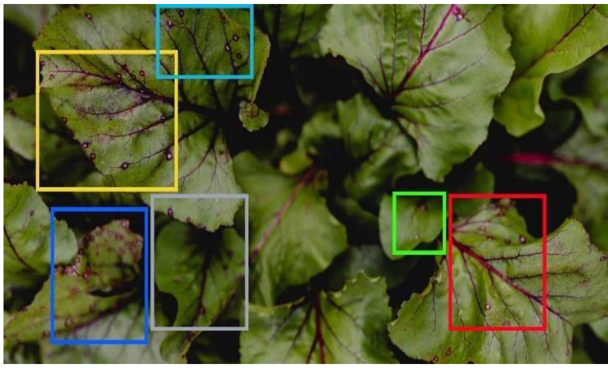
- High Accuracy: shows that the model's ability to identify and categorize diseases is generally effective. To identify plant leaf diseases, an accuracy above 90% is typically considered good, depending on the complexity of the dataset.
- High Precision and Recall: In this case, if a model has moderate to high accuracy and moderate to high recall, it can efficiently identify diseases without creating many false alarms. In practice, if both precision and recall are high, then the model is dependable.
- Confusion Matrix Analysis: It helps find specific classes for which the model is confused. An example of two conditions that have slightly similar symptoms; a model cannot identify the two conditions, indicating the requirement for more information or for the model itself.

*C. Sample Results for Identifying Plant Leaf Diseases*

Consider a scenario where a dataset of 10,000 photos of different diseases and healthy leaves was used to train a plant leaf disease identification algorithm. Here are some hypothetical results:

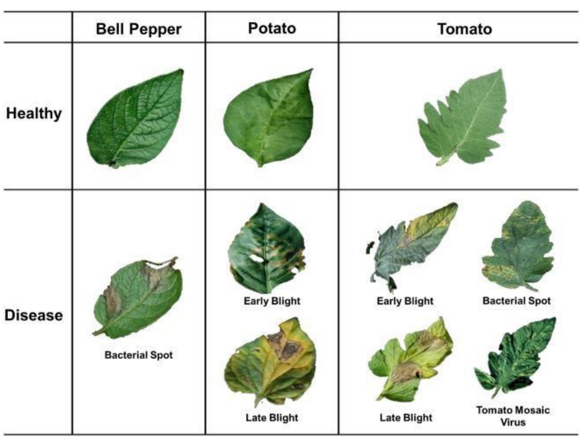
- Accuracy: 93%
- Precision: 92%
- Recall: 91%
- F1 Score: 91.5%

Analysis:



- High Accuracy: With an accuracy of 93%, the model performs well overall.
- Precision and Recall: The precision (92%) and recall (91%) indicate a good balance between sensitivity and specificity, meaning the model is both accurate and reliable.
- Confusion Matrix Insights: The confusion matrix shows most predictions are accurate, but there are some misclassifications between

  Disease A and Disease B, which might require additional data or refined features for better differentiation.




*D. Visualizations for Result Interpretation*

- ROC Curve (Receiver Operating Characteristic): The Receiver Operating Characteristic curve displays a trade-off between true positive and false positive rates at different levels. High model performance is indicated by a curve toward the upper left corner.
- Precision-Recall Curve: Useful for evaluating models against imbalanced datasets. The larger area under the curve represents better model performance, and its abbreviation is AUC.
- Learning Curves: Show training and validation loss/accuracy over epochs to identify underfitting or overfitting. If the model overfits, you might see a large gap between training and validation curves.

*E. Possible Improvements Based on Results*

- Data augmentation: To improve generalization across cases, further augmentation techniques, including multiple rotations, flips, and zooms, can be tried to increase diversity in the training data.
- Model Fine Tuning: Perform hyperparameter tuning or experiment with other architectures, which may yield even enhanced accuracy and reduced mistake results, including deeper CNNs and ensemble methods.
- Class Rebalancing: In the case that there are few examples of some of the diseases, perform class balancing using techniques such as under- or over-sampling, or even the creation of synthetic data (such as SMOTE).

## V. CONCLUSION

As important as proper treatment is, machine learning for plant leaf disease identification can totally change the way farmers facilitate early and accurate disease detection. The models are reliable resources for farmers and agricultural professionals because they have shown a massive capacity to differentiate between other illnesses and healthy circumstances. It is actually a few of the performance metrics that define high performance within the broader scope of machine learning: namely, accuracy and precision with recall. When deployed on user-friendly platforms like web or mobile applications, this significantly impacts large potential for scalable real-time monitoring and diagnostics to support precision agriculture and sustainable farming practices.

Despite these promising results, there are a few gaps that have to be cautiously filled to further strengthen the robustness and generalization capability of the models. This includes enhancing differentiation by the model between diseases that belong to similar visual manifestations, as well as consistency in performance given different environmental conditions and varieties of plants. This could be realized by including more representative and diverse datasets, using advanced complex models such as ensemble methods or deeper neural networks, and leveraging transfer learning and domain adaptation. Secondly, continuous model monitoring with periodic retraining using new data will be required for maintaining the effectiveness of the model through changes in disease patterns over time.

The power of machine learning in detecting diseases affecting plant leaves has great benefits related to accuracy, efficiency, and scalability. Farmers are empowered to take technology-driven insights for better farming and healthier crops, contributing to sustainable agriculture. More research and development is needed at this point to overcome the challenges that exist today before the full benefit of Plant health management can benefit from the application of this promising field of machine learning.

## VI. FUTURE SCOPE

Plant leaf disease detection happens to be the area of machine learning where this holds promise for agriculture: the earlier the possibility of detection of diseases, perhaps with speed, accuracy, and ease. It is envisioned that with the advent of more diverse datasets, further away in the future, machine learning models can identify a diversity of diseases in many crops and settings.

Future advancements may involve integrating these models with technologies like drones, smartphones, and IoT devices, enabling real-time, on-site disease detection and management. Additionally, combining image data with other agricultural data such as soil quality and weather patterns) could result in comprehensive systems that provide early warnings and actionable insights, helping farmers make more informed decisions. Ultimately, these innovations could contribute to more sustainable farming practices, increased crop yields, and better food security globally.

Common problems include actual cultivation circumstances, a cluttered field background, uneven illumination, and inability to identify plant diseases in other parts of the plant images. Thirdly, make use of your knowledge of hyperparameter adjustment, ensemble techniques, and the range of pooling processes [28].Fourthly, if the forecast was made using deep learning techniques, the prediction system would require a colossal amount of resources [25]. Therefore, it is important to create squeeze models for use in robotics, UAVs, drones, and mobile phones.

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