CARDAMOM AND GRAPE LEAF DISEASE DETECTION APPROACH USING CONVNEXTXLARGE

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ABSTRACT

Cardamom is one of the most popular spices in the world. In India, it is primarily grown in the evergreen forests of Karnataka, Kerala, Tamil Nadu, and the northeastern regions. India ranks third among the world's top three producers of cardamom. Plant diseases have a catastrophic impact on food production and safety, reducing both the quality and quantity of agricultural products. In severe cases, plant diseases can lead to significant losses or even a complete harvest failure. Various diseases and pests affect the growth of cardamom plants at different stages, impacting crop yields. Our work focuses on two diseases affecting cardamom plants: *Colletotrichum Blight* and *Phyllosticta Leaf Spot*, as well as three diseases of grape: *Black Rot*, *ESCA*, and *Isariopsis Leaf Spot*. Various methods have been proposed for plant disease detection, with deep learning emerging as the preferred approach due to its remarkable performance. In our work, U2-Net was utilized to remove the unwanted background from input images by selecting multiscale features. This work proposes a cardamom plant disease detection approach using the ConvNeXtXLarge model. Our experimental results demonstrated that the proposed approach achieved a detection accuracy of 93.35%.

Keywords: Deep Learning, ConvNeXtXLarge, Cardamom Leaf Disease, Graph Leaf Disease

1. INTRODUCTION

Cardamom is widely used as a flavoring agent and is also extensively utilized in medicine, including both allopathy and Ayurveda (Manju *et al.,* 2018). It is considered a highly profitable crop, and modern agro-production technologies have been developed and widely adopted across all cardamom-growing regions in India. However, the spread of various pests and diseases remains a significant challenge and a major production barrier for the cardamom sector. Small cardamom is susceptible to numerous pathogenic bacteria, which can severely damage the crop and cause significant harm. Diseases affecting cardamom plants, such as *Colletotrichum Blight* and *Leaf Spot*, frequently occur in fields where proper crop management practices are not implemented (Manju *et al.,* 2018).

The emergence of plant diseases significantly affects agricultural production. If plant disorders are not diagnosed in time, food scarcity could worsen (Fina *et al.,* 2013). Plant diseases, pests, and weeds pose threats to production and quality farming, resulting in both crop and economic losses, accounting for approximately 15–25% of food production in India (Mahlein *et al.,* 2018). Various other factors, such as climate change and modern cultivation techniques involving the excessive use of chemical fertilizers, further degrade the quality and quantity of agricultural products. Infected plants often exhibit visible signs or lesions on leaves, trunks, flowers, or fruits. Typically, each disease or pest infestation creates a unique visual pattern that can be used to identify anomalies. Among plant parts, leaves are particularly significant in diagnosing diseases, as the earliest visible symptoms often appear on them (Ebrahimi *et al.,* 2017).

Traditionally, agricultural and plant pathology experts visit farmland or farmers to identify plant disorders and pests based on their experience and knowledge. However, this approach is not only simplistic but also inefficient and prone to errors. Agriculturists with limited knowledge may misdiagnose the issue and apply pesticides or insecticides indiscriminately during the screening process, leading to unnecessary economic losses (Manso *et al.,* 2019). To address these challenges, employing image processing through an automatic plant leaf disease detection approach is crucial (Singh *et al.,* 2017). Timely detection forms the foundation for effective prevention and management of plant leaf diseases, playing a vital role in the supervision and decision-making processes in agricultural production.

In a recent study, computer vision and machine learning-based techniques were developed for plant leaf disease detection. Real-time plant disease detection faces significant challenges (Pourreza *et al.,* 2015), including complex backgrounds and varying disease severity due to images captured directly from farm fields. This study proposed a method for detecting cardamom plant diseases. Cardamom plant leaf images were captured in farm fields with complex backgrounds, and a dataset was generated to evaluate the detection capability of the proposed approach. The U2-Net architecture (Qin *et al.,* 2020) was employed in this work to leverage multiscale features for background removal. Additionally, state-of-the-art deep learning models, such as ConvNeXtXLarge (Tan *et al.,* 2021), were utilized to enhance the detection process.

U2-Net (pronounced "U-squared-Net") is a deep learning model for image segmentation, introduced by researchers at Wuhan University and Microsoft Research Asia in 2020. The model is designed to perform accurate and efficient segmentation of complex images, including those containing multiple objects and intricate backgrounds. U2-Net is based on the U-Net architecture, a widely used convolutional neural network for image segmentation. The U-Net architecture consists of two main components: a contracting path, which downsamples the input image to extract features, and an expanding path, which upsamples these features to generate a segmentation map. U2-Net enhances the U-Net architecture by introducing several innovative features and modifications. A key feature of U2-Net is the U2 block, a refined version of the U block used in the original U-Net. The U2 block comprises two convolutional layers followed by a concatenation operation, enabling the model to effectively capture both low-level and high-level features from the input image. These enhancements make U2-Net particularly suitable for segmenting images with complex and detailed structures.

Another important modification introduced by U2-Net is the multi-level feature fusion module, which combines features from different levels of the network to enhance segmentation accuracy. This module consists of several convolutional layers and skip connections, enabling the model to capture both local and global context. U2-Net also utilizes a lightweight decoder network, which reduces the model's parameter count and improves its efficiency. This is achieved through the use of depthwise separable convolutional layers, which decompose the convolution operation into separate depthwise and pointwise convolutions. The model achieves state-of-the-art performance while remaining lightweight and computationally efficient, making U2-Net a promising model for a wide range of applications, including image segmentation, object detection, and image classification.

ConvNeXt is a deep neural network architecture proposed by Facebook AI

Research in 2018. It is designed to enhance the performance of convolutional neural networks (CNNs) by combining group convolutions and concatenation. Variations of the original ConvNeXt architecture, including ConvNeXtTiny, ConvNeXtSmall, ConvNeXtBase, ConvNeXtLarge, and ConvNeXtXlarge, differ in depth and width. These models have achieved state-of-the-art performance on various image classification benchmarks, including ImageNet. The use of group convolutions and concatenation reduces the number of parameters and computational requirements, making the network more efficient and scalable. ConvNeXt has been widely applied in various computer vision tasks, such as object detection and segmentation.

The main objective of using ConvNeXtXLarge for cardamom and grape leaf disease detection is to remove the complex background, producing results without degrading the quality of the original image. This approach also aims to improve classification accuracy and reduce processing time.

U^2-Net is a deep learning architecture specifically designed for image segmentation, which involves identifying and separating different objects and regions within an image. The goal of U^2-Net is to provide a highly accurate and efficient method for image segmentation, applicable to a wide range of tasks, including medical imaging, autonomous driving, and more.

ConvNeXt is a pure ConvNet model introduced in the paper “A ConvNet for the 2020s.” The model is designed to be accurate, efficient, scalable, and simple in design. It is built entirely from standard ConvNet modules and can be applied to image classification, object detection, and segmentation tasks.

2. DATASET COLLECTION

A total of 1,724 images of cardamom plant leaves have been collected, categorized into three classes: *Colletotrichum Blight*, *Phyllosticta Leaf Spot*, and healthy leaves. These categories were assigned with the assistance of officers from the Indian Cardamom Research Institute, Regional Station Sakaleshpur, Karnataka, a branch of the Spices Board of India. Additionally, the grape disease dataset from the PlantVillage dataset, containing three types of grape diseases—*Black Rot*, *ESCA*, and *Isariopsis Leaf Spot*—has been utilized.

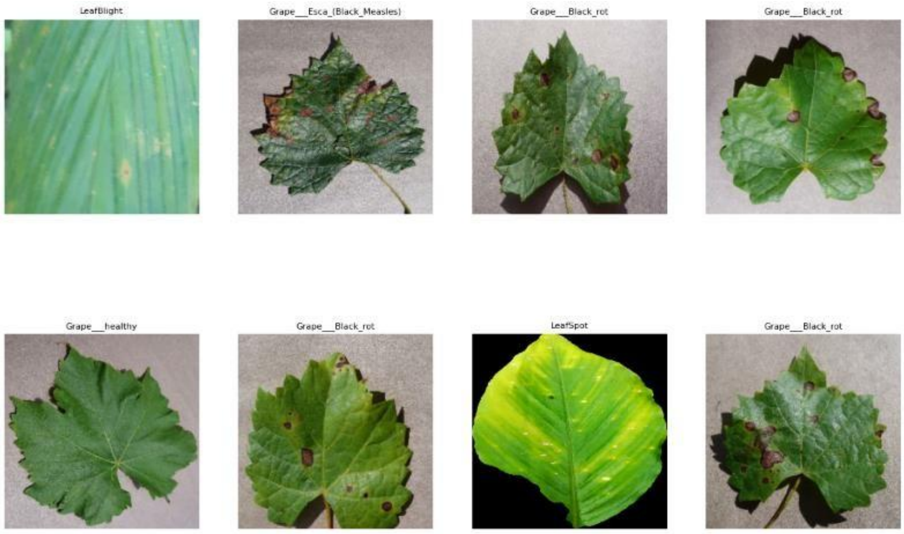


Figure 2.1 Cardamom and Grape Leaf

3. SYSTEM METHODOLOGY

In our proposed system (figure 3.1), a cardamom plant leaf disease detection approach is introduced by employing a background removal technique using U²-Net to eliminate the complex background of the image. The EfficientNetV2 deep learning model is used for classification. The input image is processed to produce a mask of the region of interest. A bitwise operation is then applied on the original image and the mask produced by U²-Net. For classification, EfficientNetV2 models were trained from scratch rather than using pre-trained weights, to classify the leaf diseases.

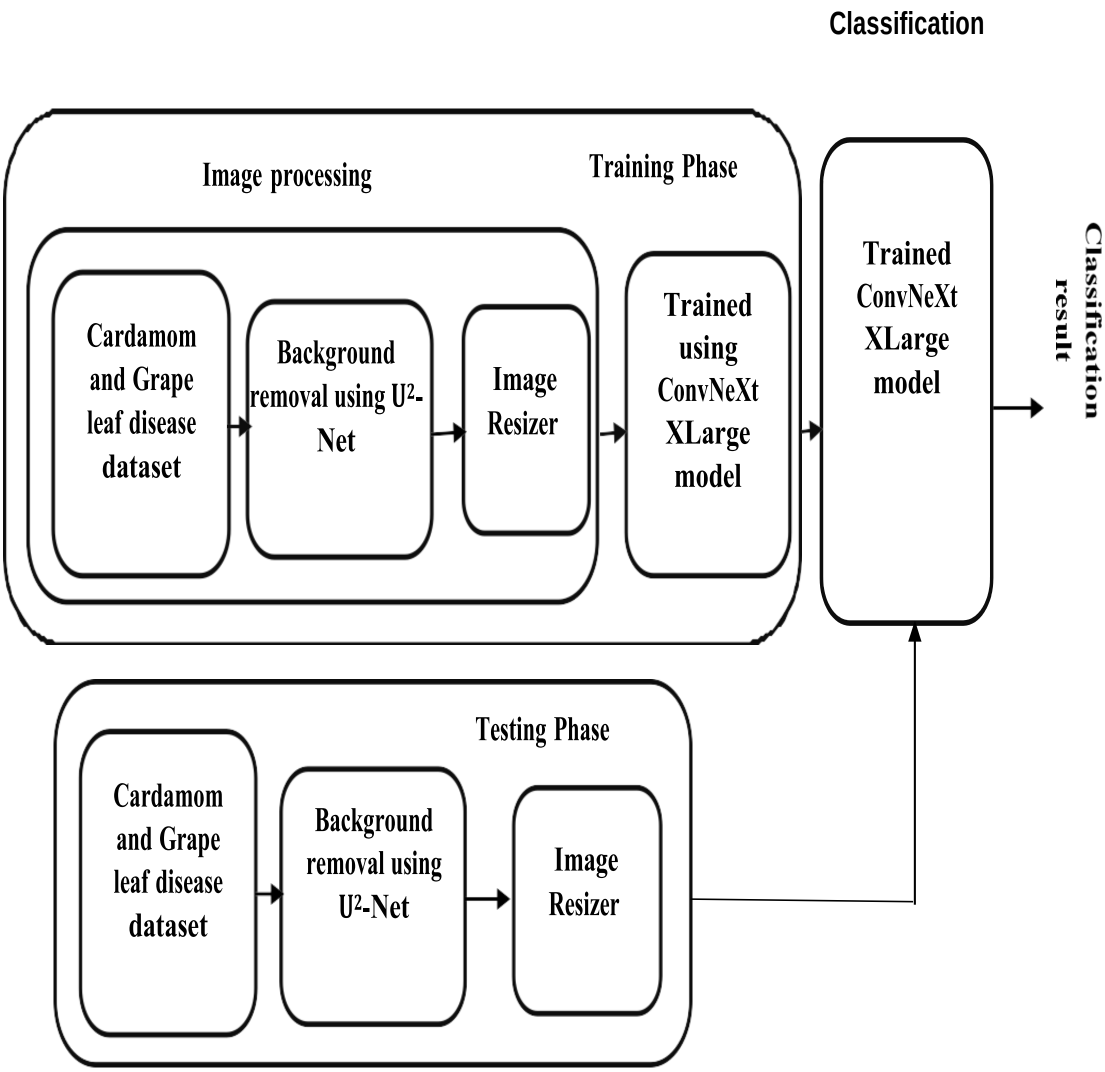


Figure 3.1 System Architecture

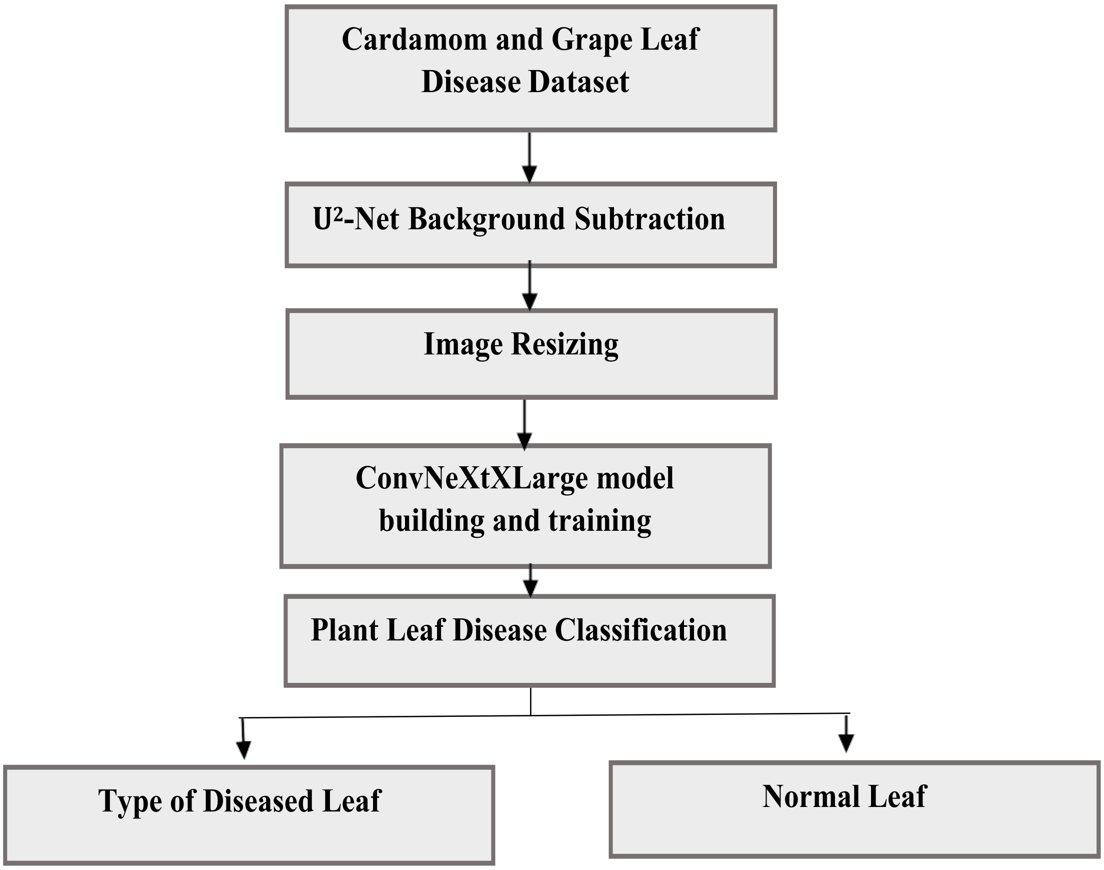


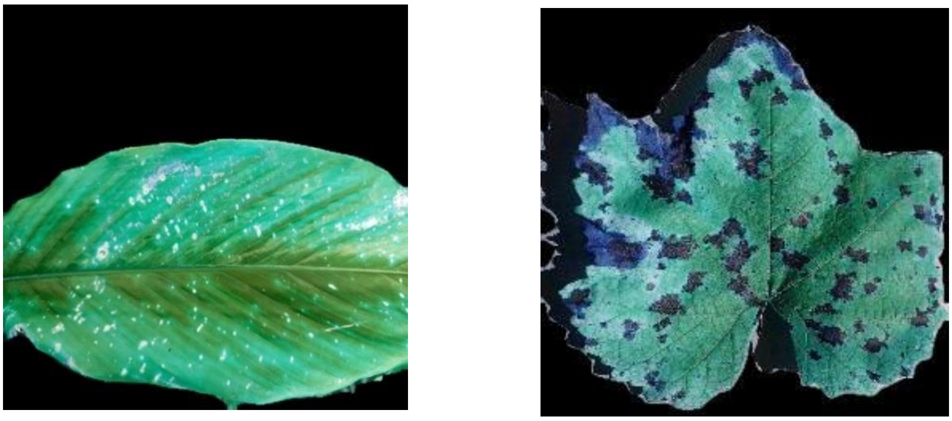
Figure 3.2 Block Diagram

3.1.1 Background Removal using U^2-Net:

Cardamom plant leaf images are of RGB, collected with a complex background with different dimensions and resolution, and the leaf is surrounded by several other factors, generally in the environment. It takes the input image to produce a mask of the region of interest. Further, it applies a bitwise operation on the original image and the mask produced by U^2-Net. U^2-Net architecture is a twofold interlaced U-structure. It consists of 3 parts. The first part is a six-stage encoder; in this stage, it uses a ReSidual U-Block (RSU). Extricate local features, an input convolutional layer generates the intermediate activation map FM(x), nextis encoder-decoder, which is like U-Net that takes FM(x) as input. The second partof the U^2-Net architecture is a five-stage decoder that uses the dilated version of the RSU. In third part saliency probability maps were generated by attaching the decoder stages to the encoder stage. Finally we remove the background parts from the given image.

(a) (b)

Figure 3.3 (a) Cardamom leaf with Background (Phylosticta Leaf Spot) (b) Grape leaf with Background (Isariopsis Leaf Spot)



(a) (b)

Figure 3.4 (a) Cardamom leaf Background Removal (Phylosticta Leaf Spot) (b) Grape leaf Background Removal (Isariopsis Leaf Spot)

3.1.2. Resizing image

Resizing images is a crucial preprocessing step in leaf disease detection and computer vision tasks in general. It serves several important purposes, each contributing to the overall effectiveness of the image analysis. Here’s a detailed explanation of why resizing images is essential in leaf disease detection:

- *Uniform Input Size:* Resizing ensures that all input images have the same dimensions, which is necessary for feeding images into deep learning models that typically require fixed input sizes.
- *Computational Efficiency:* Smaller images are less computationally demanding, making it easier for deep learning models to process them. This is especially important when handling high-resolution images.

- *Memory Management:* Smaller images consume less memory, which is crucial when working with limited GPU or RAM resources. Resizing helps prevent out-of-memory errors during model training and inference.
- *Consistency in Features:* Resizing preserves the relative proportions and features of objects within the image, ensuring that important patterns and structures remain consistent, even when the overall size is altered.

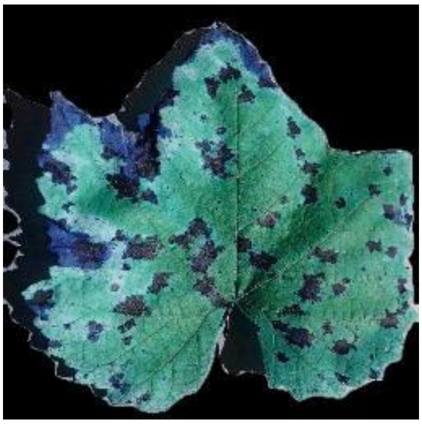
(a)  **(b)** 

Figure 3.5 (a) Resized Cardamom leaf (Phylosticta Leaf Spot) (b) Resized Grape leaf (Isariopsis Leaf Spot)

3.1.3 ConvNextXLarge model

ConvNeXt is a deep neural network architecture designed to enhance the performance of convolutional neural networks (CNNs) (Hang *et al.,* 2019) by utilizing a combination of group convolutions and concatenation. These models have achieved state-of-the-art performance on various image classification benchmarks, including ImageNet. The use of group convolutions and concatenation helps reduce the number of parameters and computational resources required to train the network, making it more efficient and scalable. ConvNeXt has been widely applied in various computer vision tasks, such as object detection and segmentation.

To build the plant leaf disease detection model using ConvNeXtXLarge, the first step is to preprocess the dataset by resizing the images to a standard size and normalizing the pixel values. The dataset is then split into training and validation sets, with the ConvNeXtXLarge model trained on the training set using an appropriate loss function and optimizer. During training, the model's weights are adjusted based on the error between the predicted outputs and the true labels. The objective is to minimize the error, or loss, by updating the weights through backpropagation. This process is repeated for several epochs, with the model's performance on the validation set being used to monitor progress and prevent overfitting.

4. RESULTS

The use of U²-Net for background removal helps to isolate the leaf region of interest, which improves the accuracy of disease detection. The EfficientNetV2 deep learning model has also shown promising results in image classification, making it an excellent choice for detecting leaf diseases. The use of deep learning algorithms allows for rapid and automated processing of large amounts of data, which can significantly reduce the time and resources required for disease detection. The proposed system is cost-effective as it does not require expensive equipment or expert knowledge to operate.

4.1. Testing

Once the model is trained, it can be used to make predictions on new, unseen images of plant leaves. The model's output provides the probability for each class, and the predicted class is the one with the highest probability.

4.1.1. Performance Evaluation:

For classification tasks, common metrics include accuracy, precision, recall, and the F1 score. Accuracy measures the proportion of correctly classified samples, while precision and recall assess the fraction of true positives among all positive predictions and among all true positives, respectively. The F1 score is the harmonic mean of precision and recall, providing a balanced measure. It combines both precision and recall to give a single evaluation metric. The accuracy metric, on the other hand, calculates the proportion of correct predictions made by the model across the entire dataset.

4.1.1.1. Accuracy

Accuracy is the most common metric used in everyday discussions. Accuracy answers the question, "Out of all the predictions we made, how many were true?" The formula to calculate the accuracy of the leaf disease classification is given by:

$$Accuracy = \frac{true\ positives + true\ negatives}{true\ positives + true\ negatives + false\ negatives + false\ positives} \quad (4.1)$$

4.1.1.2. Precision

Precision is a metric that gives the proportion of true positives to the total number of positive predictions made by the model. It answers the question, “Out of all the positive predictions we made, how many were true?” The formula to calculate the precision of the leaf disease classification is given by:

$$Precision=\frac{true\ positives}{true\ positives+false\ positives} \qquad (4.2) \qquad (4$$

4.1.1.3. Recall

Recall focuses on how well the model identifies all the positive instances. Also known as the true positive rate, recall answers the question, “Out of all the data points that should be predicted as true, how many did we correctly predict as true?” The formula to calculate the recall of the leaf disease classification is given by:

$$Recall = \frac{true\ positives}{true\ positives+false\ negatives} \qquad (4.3)$$

4.1.1.4. F1 Score

The F1 score is a metric that combines both recall and precision. Since there is often a trade-off between precision and recall, the F1 score can be used to measure how effectively the model balances this trade-off. The formula to calculate the F1 score of the leaf disease classification is given by:

$$F1= 2*\frac{precision*recall}{precision+recall} \qquad (4.4)$$

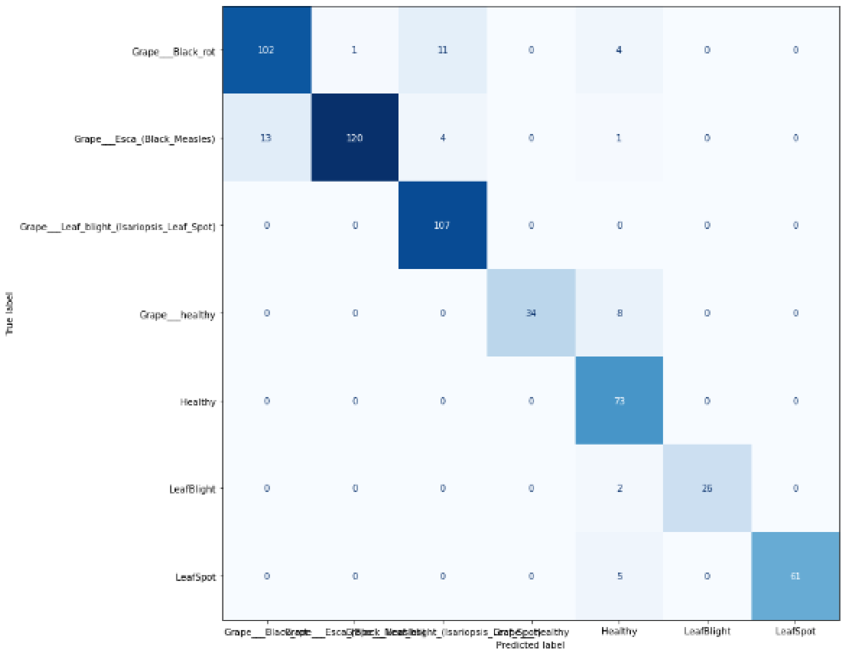


Figure 4.1 Confusion matrix for Cardamom and Grape Leaf disease

One important feature of the F1 score is that the result becomes zero if either of the components (precision or recall) is zero. This penalizes extreme negative values of either component, reflecting the model's inability to balance both precision and recall effectively.

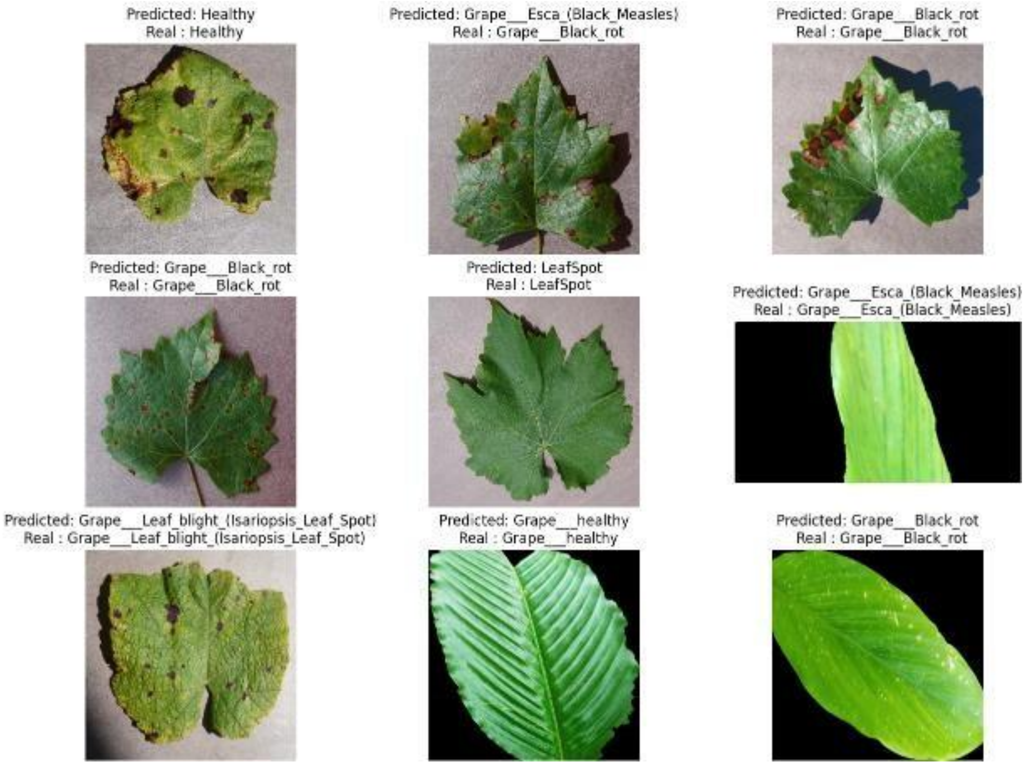


Figure 4.2 Predicted output for Cardamom and Grape Leaf disease

5. CONCLUSION AND FUTURE ENHANCEMENT

5.1. Conclusion

An efficient plant leaf disease detection approach is crucial for real-time identification of plant diseases. In this context, a cardamom plant leaf disease detection method was proposed, where the dataset of cardamom plant leaves was collected from farmland with a complex background. Segmenting and detecting diseases in real-time images is a challenging task due to factors such as the image background, lighting conditions, and the angle at which the images are captured. In the proposed method, the U2-Net architecture is utilized to remove the complex background, yielding results without compromising the quality of the original image. For classification, the ConvNeXtXLarge model was trained from scratch, rather than using pre-trained weights, to improve the detection accuracy of the cardamom plant dataset during external testing. Our experimental results demonstrated that the proposed approach achieved a detection accuracy of 93.35%, confirming the effectiveness of the method in real-time plant leaf disease detection.

5.2. Future Enhancement

In future work, we aim to enhance classification accuracy by incorporating the Inception-ResNet-V2 model. This model utilizes residual connections to address the vanishing gradient problem, allowing the network to learn more complex features and improve overall performance. The architecture consists of deep convolutional layers, pooling, and activation functions, along with auxiliary classifiers at intermediate layers to encourage the network to learn more discriminative features. We also plan to train the model using large datasets such as ImageNet, which will help improve its robustness. By leveraging this advanced model, we expect to achieve state-of-the-art performance on image classification benchmarks like ImageNet and COCO. This will further benefit the plant leaf disease detection task by improving both the accuracy and the overall robustness of the detection system.

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