

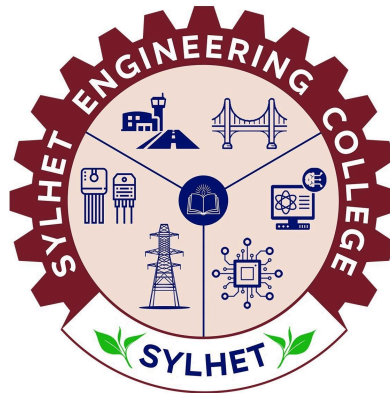
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Bean leaf disease classification using Deep learning approach in Sylhet region.

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This is to certify that the work presented in this thesis, titled “**Bean leaf disease classification using Deep learning approach in Sylhet region,**” is the outcome of the investigation and research carried out by us under the supervision of Md Lysuzzaman. It is also declared that neither this thesis nor any part thereof has been submitted anywhere else for the award of any degree or diploma.

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Abstract

Bangladesh is an agricultural country. Many crops are cultivated in Bangladesh. In Sylhet division beans are cultivated widely. In the Sylhet region, beans play a huge role in agricultural production. But it is a huge matter of concern that there are many diseases that affect the bean and cause huge problems for farmers. That's why disease should be effectively managed and controlled to prevent this loss. For suitable cultivation and reduced cost system disease should detect the early stage of disease. To help this early detection this paper proposed an automated disease detection system by using deep learning model. Here we use pretrain CNN model MobileNetV2, EfficientNetV2, DenseNet121, VGG19 to train our own private data. Here we have use to class o private data also among total eight class of data. Rest of six class data we have collected from different crop fields of sylhet division. We use tensorflow to train and access models. This study explains how efficiently we can use CNN model to classify disease, to ensure increasing crop productivity.

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Chapter 1

Introduction

The foundation of the economies of many emerging nations, including Bangladesh is agriculture. Crop health is essential to maintaining food security and economic stability in areas like Sylhet, where a sizable section of the populace makes their living from farming. Beans are a significant legume among the many crops grown in the area, and they are grown extensively for both their nutritional and commercial benefits. In Bangladesh, seven types of vegetables occupy 56% of the total cultivated area, and the country bean is one of the most important of these vegetables [1]. However, bean plants are extremely susceptible to a number of diseases, including angular leaf spot and bean rust, just like many other crops. A report revealed that eighteen species of insect cause infestation on country bean fields [2]. Bean pods provide vitamins (vit A, vit C, riboflavin, hiamine) and different minerals, i.e., magnesium, calcium, phosphorous, potassium, iron, sulfur, and sodium [3], [4] . In addition to being labor-intensive and time-consuming, this process is also subject to subjectivity and human error. Furthermore, early diagnosis becomes much more difficult in rural locations where professional guidance may not always be easily accessible. The process of detecting plant diseases through image-based analysis can now be automated thanks to technological advancements, especially in the areas of computer vision and deep learning. A branch of artificial intelligence called deep learning has demonstrated impressive results in tasks like object segmentation and image categorization. It is now possible to train accurate models with comparatively small datasets by utilizing transfer learning techniques and pre-trained convolutional neural network (CNN) models. The creation of a deep learning-based system to categorize and divide up bean plant diseases in the Sylhet area is the main goal of this thesis. The study trains and assesses some pre-trained CNN models—MobileNetV2, EfficientNetV2, DenseNet121 and VGG19—using a dataset of annotated bean leaf images. In order to improve crop management, lower losses, and boost agricultural productivity in Sylhet, the suggested method seeks to provide local farmers with a workable, real-time option for early disease identification.

1.1 Background

Bean crops are a significant source of both food and revenue in areas like Sylhet, where agriculture plays a major role in the economy. Bean diseases can significantly lower crop yields and affect bean plants. Disease detection has always depended on labor-intensive and frequently

imprecise manual observation. The effectiveness of automated plant disease identification has increased with developments in deep learning and computer vision. Plant diseases can be accurately identified and localized thanks to Convolutional Neural Networks (CNNs), which are extensively utilized for picture classification. Transfer learning makes deep learning more accessible for real-world applications by enabling the use of previously trained models on smaller agricultural datasets. Despite these developments, the Sylhet region has seen little use of these technologies for indigenous crops. By creating a deep learning-based system for categorizing and segmenting bean leaf diseases, this thesis seeks to close that gap and assist farmers in taking prompt, well-informed crop protection measures.

1.2 Problem statement

Diseases like bean rust, bean yellow mosaic virus, tobacco caterpillar, leaf curl, leaf miner, cercospora leaf spot and angular leaf spot commonly afflict bean fields in the Sylhet region, resulting in large yield losses and financial difficulties for nearby farmers. Manual inspection is the foundation of traditional disease detection techniques, but it is frequently imprecise, time-consuming, and unavailable to remote areas. Effective treatment and control of plant diseases depend on early and precise identification; yet, automated, intelligent solutions that are adapted to regional agricultural requirements are lacking.

In the Sylhet region, there is little study and application especially devoted to bean disease diagnosis, despite deep learning's demonstrated promise in plant disease detection using picture classification. In the Sylhet region, diseases including bean rust, bean yellow mosaic virus, tobacco caterpillar, leaf curl, leaf miner, cercospora leaf spot and angular leaf spot commonly impact bean fields, resulting in large yield losses and financial difficulties for nearby farmers. Conventional disease classification techniques depend on manual inspection, which is frequently imprecise, time-consuming, and unavailable to remote people. For plant diseases to be effectively treated and prevented, early and precise identification is essential. However, automated, intelligent solutions that are suited to regional agricultural requirements are lacking.

1.3 Motivation

For many people in the Sylhet region, agriculture continues to be their major source of income, and growing beans is essential to both guaranteeing food security and making money. However, crop health and productivity are seriously threatened by the prevalence of diseases like angular leaf spot, bean rust etc. Early disease detection and response are challenging for many farmers due to a lack of timely expert advice.

Deep learning and computer vision's expanding capabilities offer a significant chance to revolutionize conventional farming methods. It is feasible to create intelligent, image-based systems that can accurately and automatically identify and categorize plant diseases by utilizing these technologies. These kinds of technologies can help farmers make well-informed decisions, save time, and drastically lessen the need for manual diagnostics.

The goal of this thesis is to use contemporary AI methods to address practical farming issues that local farmers encounter. Farmers in Sylhet can be empowered to safeguard their crops, increase production, and support the region's economic stability by creating an easily accessible, precise, and region-specific system for bean disease identification and segmentation. Additionally, this effort supports more general objectives of using technology to advance sustainable development and smart agriculture.

1.4 Research Area

Precision agriculture for precise and timely disease management; deep learning, specifically the use of Convolutional Neural Networks (CNNs) for disease classification; computer vision techniques for image classification, transfer learning by adapting pre-trained models like MobileNetV2, EfficientNetV2, DenseNet121 and VGG19, agricultural informatics, with an emphasis on technology-driven crop health monitoring; and a regional focus on applying these AI-based methods specifically to bean crops in the Sylhet region are all areas of research covered in this thesis.

1.5 Research Aim

Using image data gathered from the Sylhet region, this thesis aims to create an automated deep learning-based system for the classification of bean diseases, notably bean rust, bean yellow mosaic virus, tobacco caterpillar, leaf curl, leaf miner, cercospora leaf spot and angular leaf spot. The method uses sophisticated Convolutional Neural Network (CNN) models and transfer learning techniques to precisely identify the disease kind and locate the affected areas on bean

plants. Through useful, AI-powered solutions catered to local farmers' requirements, our research seeks to enable early diagnosis, minimize crop loss, and advance smart agriculture.

1.6 Research objectives

- To gather and compile a dataset of photographs of bean leaves from the Sylhet region, including samples that are bean rust, bean yellow mosaic virus, tobacco caterpillar, leaf curl, leaf miner, cercospora leaf spot and angular leaf spot and healthy.
- Pre-trained deep learning models MobileNetV2, EfficientNetV2, DenseNet121, and VGC19 will be used and assessed in order to classify bean leaf diseases via transfer learning.
- Use classification measures including the Dice coefficient, accuracy, precision, recall, and F1-score to evaluate the performance of many CNN models.
- To examine how various optimization methods affect model performance for better disease identification.
- In order to helping farmers in the Sylhet region by offering a useful and effective deep learning-based solution for real-time bean disease diagnosis.

Chapter 2

Background Study

2.1 Convolutional Neural Networks

CNNs are a specialized type of deep learning model designed for processing visual data, particularly images. They have revolutionized computer vision by automatically learning spatial features, making them highly effective for tasks like plant disease detection. CNNs are composed of multiple layers—each with a specific function—that work together to convert input images into accurate class predictions.

2.1.1 Input Layer

The input layer takes in preprocessed bean leaf images (e.g., resized, normalized, augmented) from the Sylhet region, labeled by disease type. It prepares the data for feature extraction in the convolutional layer.

2.1.2 Convolutional Layers

The convolutional layer is the core of a CNN, using filters to automatically extract features from images, such as edges, textures, and disease patterns. Early layers detect simple shapes, while deeper ones capture complex leaf damage like spots or deformities. This process preserves spatial relationships and eliminates the need for manual feature extraction, making CNNs effective for identifying bean leaf diseases.

2.1.3 Activation Function (ReLU)

The ReLU activation function adds non-linearity to CNNs by setting negative values to zero, helping the model learn complex patterns. It improves training speed and prevents vanishing gradients. In this thesis, ReLU enhances the CNN's ability to detect subtle differences in leaf texture and color for accurate disease classification.

2.1.4 Pooling Layers

Pooling layers, especially Max Pooling, reduce the spatial size of feature maps by keeping key features and discarding irrelevant details. This lowers computation, adds spatial invariance, and helps the CNN focus on important disease patterns in bean leaf images, improving efficiency and robustness.

2.1.5 Fully Connected Layers

Fully connected layers flatten the extracted features and use dense connections to classify the input image. Acting as the CNN's final decision-making stage, they analyze complex feature relationships to predict whether a bean leaf is Healthy, or affected by diseases like Bean Rust or Mosaic Virus.

2.1.6 Output Layer

The output layer uses a softmax function to generate probabilities for each disease class, selecting the one with the highest confidence as the prediction. In this thesis, it identifies the bean leaf's condition and provides confidence levels, supporting accurate and reliable disease diagnosis.

2.2 Role of CNNs in Our Thesis

In our project, we use pre-trained CNN models—EfficientNetV2, DenseNet121, MobileNetV2, and VGG19—fine-tuned on bean leaf images from Sylhet. These models automatically extract features and classify diseases like Bean Rust, Yellow Mosaic Virus, Leaf Miner, and Healthy leaves. Their strong performance in agricultural tasks, combined with transfer learning, allows for high accuracy and faster training even with limited data, providing reliable disease predictions for farmers.

2.2.1 EfficientNetV2

The architecture of our bean disease classification system using EfficientNetV2 and transfer learning. Input images of bean leaves are passed into a pretrained EfficientNetV2 model (originally trained on ImageNet), which enables efficient and accurate feature extraction even with limited data. The model uses a series of Fused MBConv and MBConv blocks to capture complex patterns, followed by global pooling, dropout, and a fully connected layer for final classification. EfficientNetV2 was chosen for its speed, accuracy, and scalability, making it ideal for real-time plant disease detection. Its use of pretrained weights also reduces the need for large annotated datasets.

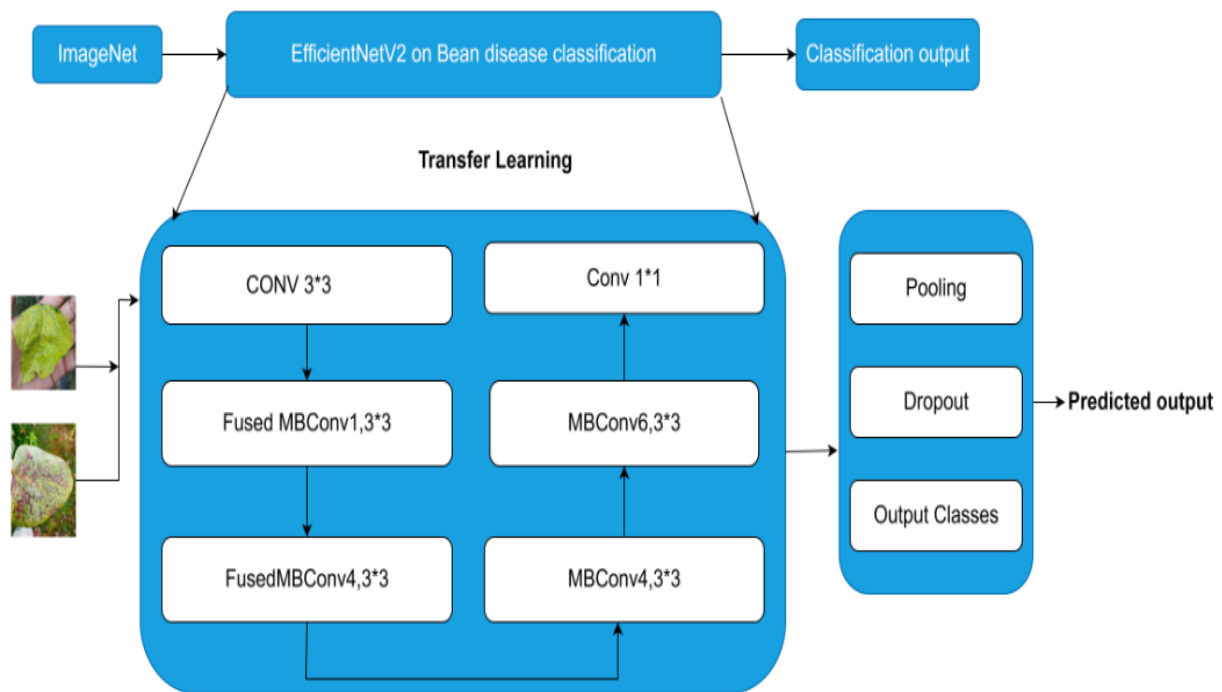


Fig 2.1 : EfficientNetV2 Architecture

2.2.2 MobileNetV2

MobileNetV2 is a lightweight CNN architecture optimized for mobile and embedded devices, using depthwise separable convolutions to reduce parameters and computational cost. In your thesis on bean disease detection in Sylhet, it enables fast, memory-efficient image processing suitable for smartphones and low-power devices. Despite its compact size, MobileNetV2 effectively identifies disease features like spots and discoloration through transfer learning tailored to your specific disease categories. Its inverted residual blocks, with pointwise and depthwise convolutions, linear bottlenecks, and shortcut connections, preserve key information while maintaining efficiency. This makes it ideal for real-time, on-field diagnostics, supporting low-cost AI tools that help farmers detect diseases early and take timely action.

2.2.3 VGG19

VGG19 plays a crucial role in your project by distinguishing visually similar bean leaf diseases through learning fine-grained patterns like subtle color changes, lesion textures, and structural deformations. Its deep architecture builds hierarchical features from simple edges to complex disease patterns, making it effective for detecting hard-to-identify symptoms. Using transfer learning, you kept the pretrained convolutional base and customized the fully connected layers for eight disease categories, improving accuracy and reducing training time. It was also part of an ensemble with EfficientNet and MobileNetV2, enhancing overall accuracy and reliability for practical, early disease detection in agricultural settings like Sylhet.

2.2.4 DenseNet121

DenseNet121 is a CNN architecture featuring dense connectivity, where each layer receives inputs from all preceding layers within a dense block, enhancing feature reuse and gradient flow while reducing parameters. It starts with a 7×7 convolution and max pooling, followed by four dense blocks with layers applying Batch Normalization, ReLU, and 3×3 convolutions. This design enables faster, more reliable training, especially with smaller datasets. In your project, DenseNet121 effectively classifies bean leaf diseases by capturing complex textures and visual symptoms, making it well-suited for real-world agricultural disease detection in Sylhet.

Chapter 3

Literature Review

In recent years, researchers have become increasingly interested in automatically classifying disease from image. But even with the efforts made, these diseases continue to be a significant obstacle to sustainable cultivation. The majority of the current disease classification and detection methodology relies solely on expert visual observation for plant disease detection, so there is still a great need for a serious procedure by a large team of specialists to continuously monitor these diseases for early stages. However, it has become clear in recent years that deep learning models with various approaches are very effective in classifying diseases.

2.1 Related works

There are many works done so far using DL model for classification and detection of bean disease as approach presented by

Bean leaf disease detection

a CNN algorithm named AlexNet model to detect either a bean leaves affected or not.[5] The model performed at accuracy 99.7% at training data set and 98.6% in the test data set.

Classify bean crop disease

[6]utilized pre-trained CNN models, GoogleNet and VGG16, to classify bean crop diseases using 1,296 leaf images (Bean Rust: 436, Angular Leaf Spot: 432, Healthy: 428) from a GitHub dataset. GoogleNet give more accuracy than VGC16 and it was 95.31%. Visualization techniques like Grad-CAM and intermediate layer activation were applied for interpretability. The dataset was split 80-20 for training/validation, with images resized (e.g., 256x256). The study did not compare model performance to human experts or evaluate real-world diagnostic impact.

Awareness about disease

Surveyed 300 country bean farmers in six Bangladeshi upazilas, using face-to-face interviews and photographs to assess pest and disease knowledge.[7] With a 6% error margin, the study found 86% male farmers (average age 38.5 years), 24% minimally literate. Aphids (99.02%) and pod borers (96.92%) were major pests, and BYMV (96.67%) and rust (85.33%) were prevalent diseases, causing 30–49% yield losses. Most used chemical pesticides at flowering, but only 5% maintained a >10-day PHI. Only 17% had pest management training, and IPM was rare. Data were analyzed with SPSS and R.

Classification of bean leaf disease

[8] utilized a dataset of 1,295 bean leaf images from Uganda, capturing Angular Leaf Spot, Bean Rust, and healthy leaves with smartphone cameras. The study applied three CNN models (MobileNetV2, EfficientNetB6, NasNet) with TensorFlow and Keras, achieving a highest validation accuracy of 91.74% using EfficientNetB6 with the Adam optimizer. The dataset was split into 1,044 training, 128 testing, and 123 validation images, but the small validation set may limit robustness. Unlike prior works, it focused on field-captured images, enhancing practical applicability, though it did not assess real-time field performance or farmer impact.

Classification of bean leaf disease

proposed a deep learning[9] approach using MobileNet architectures to classify bean leaf diseases, utilizing a public dataset from the National Crops Resources Research Institute (NaCRRI). The dataset included images of healthy bean leaves, angular leaf spot, and bean rust, achieving a validation accuracy of 97.74% with MobileNetV2 after 100 epochs. The study employed TensorFlow and Python, with experiments conducted on Google Colab using GPU acceleration. Performance metrics included precision, recall, F1-score, and accuracy, though the model faced overfitting issues due to a limited number of classes. The dataset's focus on field-captured images enhances its practical relevance, but the study did not evaluate real-time field performance or farmer impact.

Classification of bean leaf disease

This study(2024) develops a CNN model to classify common bean leaf diseases, achieving 98% training and 92.2% validation accuracy on 1,766 farmland images. This paper prior CNN and SVM use for plant disease detection, with up to 90% accuracy. Limited dataset diversity, overfitting, and non-public data restrict generalizability. Outperforming models like VGG16, the CNN shows promise but needs broader datasets and transfer learning for improved applicability.[10]

Classification of rice crop disease

[11] this paper uses YOLOv8 to classify 19 rice crop diseases in Bangladesh, leveraging a dataset of 2,850 images, augmented to 5,750. The literature review cites prior rice quality studies (e.g., Sabs et al., 2021). YOLOv8, with a ResNet-50 backbone, achieves 98% mAP and 99% F1 score. Limitations include a non-public dataset and potential overfitting. The model outperforms prior methods, aiding early disease detection.

Plant disease detection

This review DL and TL[12] for plant disease detection in Bangladesh. Hossain et al. (2021) achieved 99.55% accuracy with MobileNet, Vallabhajosyula et al. (2022) 99.99% with a Deep Ensemble Neural Network, and Shewale et al. (2023) 99.81% with CNN. Ahmad et al. (2021) and Akhter et al. (2024) report high accuracies with MobileNetV3 and EfficientNet. XAI studies by Bhandari et al. (2023) and others use GradCAM, LIME, and SHAP. The paper addresses multi-plant disease classification gaps, proposing TL and XAI for 21 leaf diseases across six plants.

Bean disease detection

The paper et al.[13] doesn't explicitly state the model's accuracy in the provided excerpts but reports a global F1 score of 97.64%, precision of 97.83%, and recall of 97.67%. For exact accuracy, refer to Table 7 or the full paper's results section.

Tomato plant disease detection

[14] This study explores machine learning-based classification of tomato plant diseases using image processing techniques. Tomato leaf images were acquired, augmented, segmented, and analyzed to extract features. Models like SVM, KNN, and decision trees were trained, with the Quadratic SVM achieving the highest accuracy of 97.7%. The approach shows promise for efficient, non-destructive disease detection in Bangladesh's tomato production.

Plant disease detection

This studies show that deep learning, especially CNNs, outperforms traditional machine learning in plant disease detection. SVM, KNN, and Random Forest have been widely used, with CNN models achieving the highest accuracy—up to 98%. However, most works used foreign datasets. This study focuses on applying CNN to common Bangladeshi crops using a relevant dataset.[15]

Bean leaf disease classification

This study presents an explainable deep learning model for classifying bean leaf diseases using a hybrid of Pyramid Vision Transformer (PVT) and GCADSN. [16] Achieving 97.66% accuracy on the Bean dataset, the model captures both global and local features and uses GradCAM for interpretability, offering a precise and transparent alternative to traditional methods.

Strawberry leaf disease classificatio

[17] In brief, ResNet50 demonstrated the highest overall performance for strawberry leaf disease classification, achieving an 88% classification accuracy during testing, alongside 88% precision, 87% recall, and an 88% F1 score. It excelled in classifying the healthy class. ResNet101 followed with an 82% accuracy, 81% precision, 85% recall, and an 83% F1 score. ResNet152 recorded an 80% accuracy, 72% precision, and an 83% F1 score, notably achieving 100% recall for the diseased class, indicating its strength in identifying diseased samples.

Tomato leaf disease classification

The performance of the Bayesian optimized deep hybrid learning models was primarily evaluated using statistical classification metrics such as accuracy, precision, recall, f1-score, and

Matthew's correlation coefficient (MCC).[18] Among the seven hybrid models, the CNN-Stacking model demonstrated the highest classification performance. On an unseen dataset, this model achieved average scores of 98.533% for precision, 98.527% for recall, 98.525% for f1-score, 98.268% for MCC, and 98.527% for accuracy. These results indicate the model's robustness, strong generalisation capabilities with minimal gaps between training and testing accuracies, and excellent class discrimination.

Five major tomato diseases classification

This study developed an automated [19] system using Convolutional Neural Networks (CNNs) to identify and classify five major tomato diseases (Bacterial Spot, Black Mold, Gray Spot, Late Blight, and Powdery Mildew) as well as healthy leaves. It involves extracting colour, shape, and texture features from segmented images, achieving a high classification accuracy of 98%. The aim is to provide a lightweight framework for early disease prediction to help prevent crop losses.

Potato disease classification

The Convolutional Neural Network's performance in classifying potato diseases was primarily assessed using accuracy and error rate. The best-trained model, which utilised 90% of the dataset for training, achieved a 96% correct classification rate (0.9585 accuracy).[20] A confusion matrix further detailed performance, showing 100% correct classification for Black Dot and Black Scurf diseases, and over 92% for Silver Scurf and Common Scab. However, the CNN showed lower performance when classifying uninfected tubers, often misclassifying them as Silver Scurf.

Potato leaf disease classification

[21] This text describes an Artificial Intelligence approach to classifying potato leaf diseases, specifically early and late blight, in addition to healthy leaves. The authors propose a deep convolutional neural network architecture with 14 layers designed for feature extraction and classification. To counter overfitting due to a relatively small initial dataset, data augmentation techniques were applied, increasing the number of images significantly. The research

demonstrates that this enhanced dataset led to a substantial improvement in testing accuracy, achieving a 98% overall mean accuracy, outperforming previous related works.

2.2 Limitations of Existing Research

The literature review revealed certain limitations in the preceding studies, including:

- The IBean dataset's restricted scope—only two illnesses and healthy leaves—reduces the model's practical efficacy despite its excellent accuracy.[16]
- [13] The model's limited dataset (1,766 pictures) restricts its real-world flexibility and ignores other significant bean illnesses outside of the three it targets, despite its great accuracy.
- Although YOLOv8 did well, its shortcomings include a tiny dataset, a concentration just on visible leaf symptoms, and[11] a lack of field testing, which might lower accuracy in real-world scenarios.
- The study's dependability and real-world application are diminished by its small sample size of four classes and absence of varied variables such as backdrop, illumination, leaf age, and temperature [22].
- [9]Generalizability is limited by the model's tiny dataset, concentration on two illnesses, high accuracy, which implies overfitting, and its exclusiveness to bean leaves.
- The generalizability of the model is limited by the short dataset (1,296 pictures) and just three classifications. Its concentration on bean leaves limits its applicability to other crops or illnesses, and the absence of field testing creates worries about overfitting.[6]

Chapter 4

Methodology

A structured pipeline is used in this study's methodology, which starts with the gathering of bean leaf photos from multiple sources, including Sylhet region-specific samples. In order to preserve only acceptable image formats like JPG, JPEG, and PNG, the gathered dataset is first cleaned by eliminating files with invalid extensions. Following cleaning, the data is categorized into eight types: angular leaf spot, rust-infected, leaf curl, leaf miner, tobacco caterpillar, bean yellow mosaic virus, cercospora leaf spot, and healthy. Data enrichment techniques, including image rotation, brightness alteration, and saturation variations, are used to improve model performance and solve dataset restrictions. By using deep learning models for disease classification, our dual-path technique increases diagnosis precision and facilitates early crop management action.

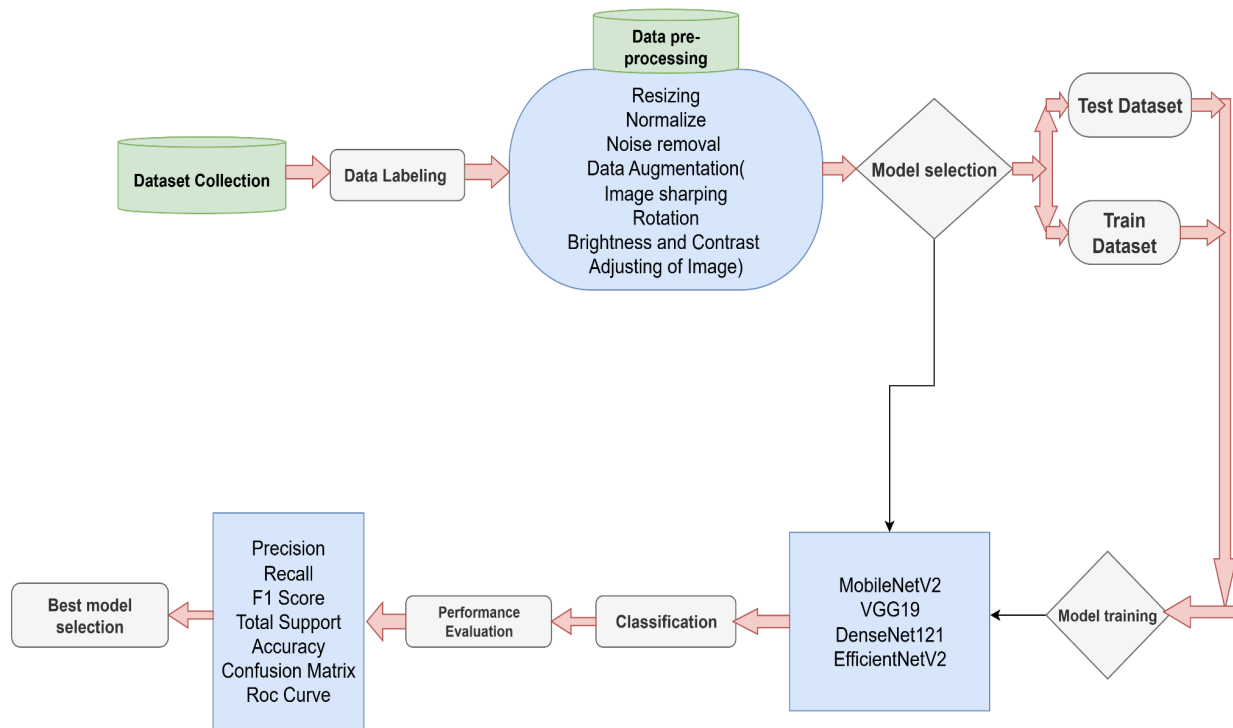


Fig 4: Diagram of Methodology

4.1 Data collection

Two primary sources of data were used in this study: field data obtained from bean farms in Bangladesh's Sylhet district and Sunamganj district and publicly available agricultural datasets. Field data are collected from different crop fields. We have collected this data by ourselves. We have used a mobile camera to collect data. Here we have used 5 different mobile devices to collect data.

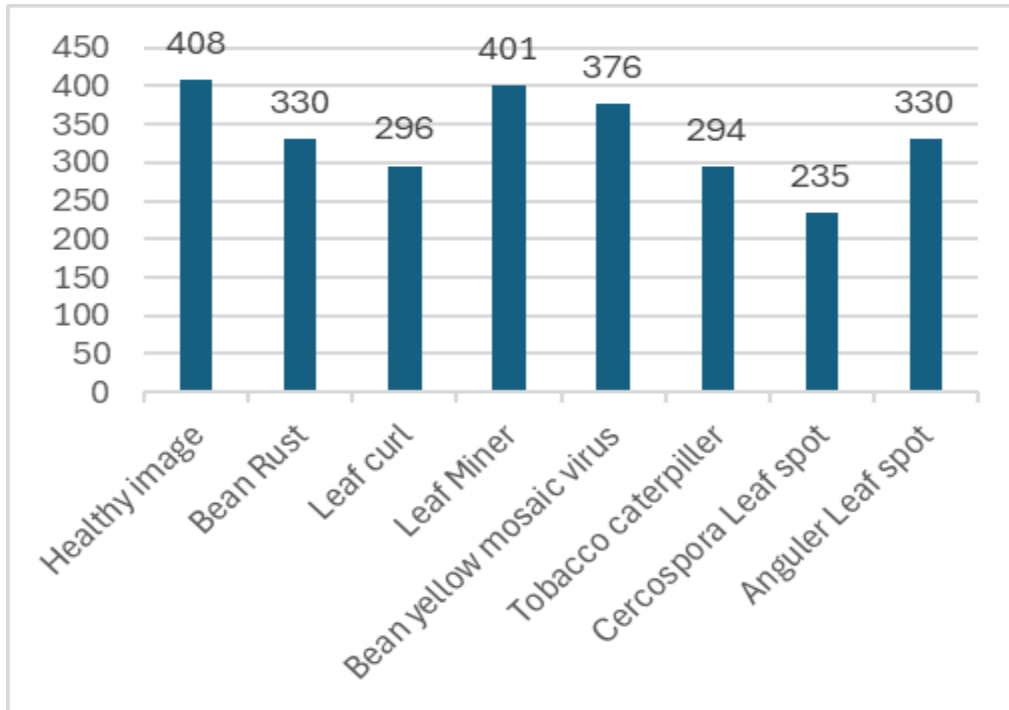


Fig 4.1.1: Disease and number of image graph

Eight classes of leaves are depicted in the pictures: angular leaf spot disease, bean rust disease, leaf curl, leaf miner, tobacco caterpillar, bean yellow mosaic virus, cercospora leaf spot and healthy leaves. Following cleaning and preprocessing, almost 2670 photos in the JPG, JPEG, and PNG file types were used. To capture variances found in the actual world, field photos were collected in natural settings. Deep learning models for disease classification were trained using this heterogeneous and geographically distinct dataset.

4.1.1 Sample Of Affected Leaves



Leaf curl

Bean Tobacco caterpillar

Cercospora leaf spot

Angular leaf Spot



BYMV

Leaf Miner

Bean Rust

Healthy Image

Fig 4.1.2: Image

4.2 Data Cleaning

The data cleaning stage plays a crucial role in preparing a high-quality dataset for training deep learning models. After collecting raw images from various sources, including public repositories and field images from the Sylhet region, the dataset undergoes a thorough cleaning process to ensure reliability and consistency.

4.2.1 Format Filtering

- Images in unsupported or irrelevant formats (e.g., `.webp`, `.gif`, `.tiff`, or corrupted files) are removed.

Only commonly accepted formats like `.jpg`, `.jpeg`, and `.png` are retained to ensure compatibility with deep learning frameworks such as TensorFlow and PyTorch.

4.2.2 Duplicate and Corrupt File Removal

- The dataset is scanned for duplicate images, which can bias model learning and evaluation. Duplicates are identified based on file name, size, or hash values and then removed.
- Corrupt or unreadable images are also discarded to avoid training errors and inconsistencies during model input processing.

4.2.3 Resolution and Quality Check

- Images with too low resolution or poor quality (blurry, overexposed, or underexposed) are excluded.
- This ensures that the remaining images have sufficient visual features for the model to learn disease patterns effectively.

4.2.4 Folder Structuring

- Cleaned images are organized into folders based on their class labels: bean rust, bean yellow mosaic virus, tobacco caterpillar, leaf curl, leaf miner, cercospora leaf spot, and angular leaf spot.
- This organization is essential for feeding the dataset into classification pipelines efficiently.

4.3 Data Labeling

The labeling stage is a fundamental part of preparing the dataset for training deep learning models. In this research, labeling was carried out in two distinct contexts: one for classification. Accurate labeling ensures that the models can learn meaningful patterns to correctly identify and locate diseases on bean leaves.

4.3.1 Labeling for Classification

- Each image is manually assigned to one of eight classes based on visible symptoms:
 - Healthy
 - Bean Rust
 - Angular Leaf Spot
 - Leaf Curl
 - Leaf Miner
 - Cercospora leaf spot
 - Bean yellow Mosaic Virus
 - Tobacco caterpillar
- This process involves careful visual inspection of the leaves to detect disease symptoms such as color changes, texture, and spot patterns.
- Images are organized into class-specific directories, which is essential for training CNN-based classification models using transfer learning.

4.3.2 Importance of Accurate Labeling

- Mislabeling during this stage can lead to poor model accuracy, especially in medical or agricultural applications where fine-grained details matter.
- Therefore, multiple rounds of quality checks and manual verification were performed to ensure labeling consistency and accuracy across the dataset.

In order to train deep learning models in classification and semantic segmentation—two crucial areas for automated disease diagnosis and decision-making assistance for farmers in the Sylhet region—this labeling procedure guarantees that the dataset is completely ready.

4.4 Data Augmentation

In this study, data augmentation is a crucial step to enhance deep learning models' performance, resilience, and capacity for generalization, particularly when dealing with small datasets. By performing different transformations that replicate changes in plant appearance found in the actual world, it creates new training samples from the existing photos.

Augmentation greatly increases the training data without necessitating further manual image collecting, given the basic dataset only includes almost 2670 images.

Common augmentation techniques used include rotation, flipping, shear image and zoom range which help the model become invariant to such variations. These transformations simulate real-world conditions like changes in leaf orientation or lighting, improving the model's robustness. As a result, the trained model is better equipped to handle diverse and unseen data during practical deployment.

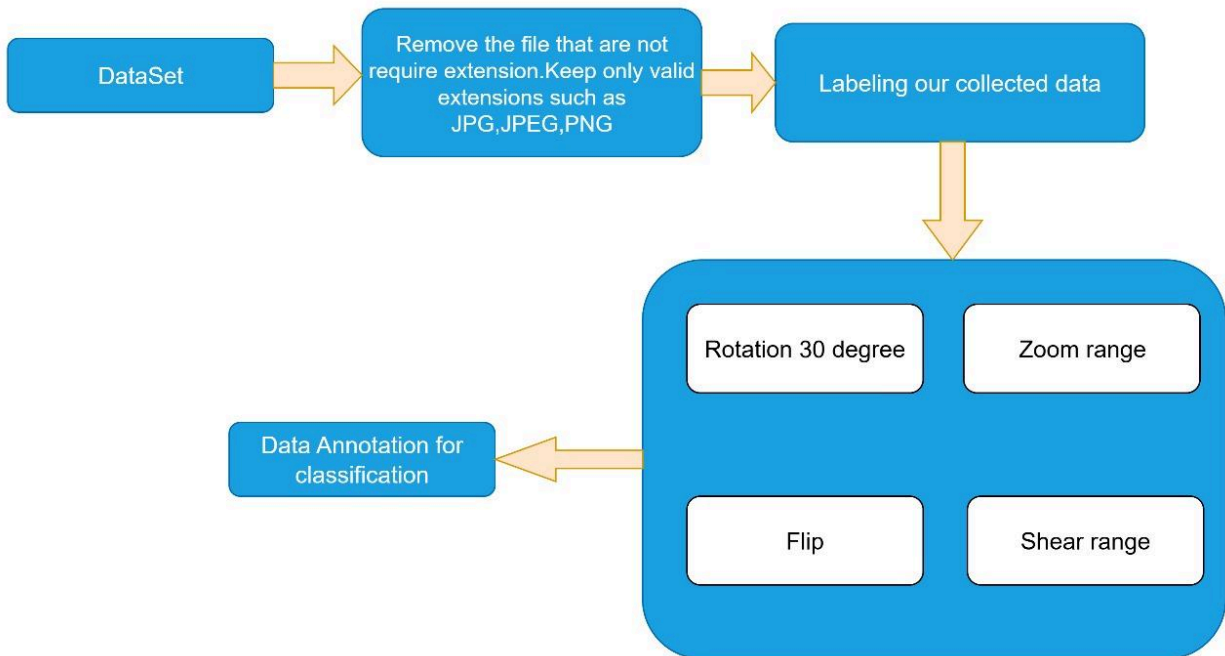


Fig 4.4.1: Augmentation Process

4.4.1 Purpose of Data Augmentation

- To prevent overfitting by exposing the model to a wider range of image conditions.
- To help the model generalize better to unseen, real-world scenarios, such as different lighting, angles, and leaf orientations.
- To simulate natural variations in bean leaf appearances due to environmental factors in the Sylhet region.

4.4.2 Augmentation Techniques Applied

The following augmentation techniques were applied to the dataset:

- **Rotation:**
 - Images were rotated at angles such as 45° (clockwise).
 - This helps the model learn that leaf orientation does not affect the disease classification.
- **Brightness Adjustment:**
 - Increased brightness by 20% and 30%.
 - Simulates conditions like strong sunlight or cloudy weather, which affect leaf visibility.
- **Saturation Adjustment:**
 - Changes in saturation help replicate different lighting and camera settings, making the model more tolerant to color variation.
- **Resizing and Normalization:**
 - All images are resized to a uniform size suitable for the input of CNN models.
 - Pixel values are normalized (scaled between 0 and 1 or standardized) to enhance training speed and consistency.

4.4.3 Result of Augmentation

- After augmentation, the effective dataset size increased multiple times, providing a rich set of diverse images for training.

- These augmented images were used for both classification and segmentation tasks, improving model performance across the board.

The study guarantees that the trained models are robust to real-world circumstances and retain excellent accuracy when used in field applications for bean disease diagnosis by methodically implementing augmentation strategies.

No	Case	Training	Validation	Testing	Total
1	Leaf Miner	1280	161	161	1602
2	Leaf Curl	947	119	119	1185
3	Bean Yellow Mosaic Virus	1203	151	151	1505
4	Tobacco Caterpillar	940	118	118	1176
5	Bean Rust	1056	132	132	1320
6	Angular Leaf Spot	1056	132	132	1320
7	Cercospora	752	94	94	940
8	Healthy Image	1221	153	153	1527
Total		8455	1060	1060	10575

Fig. 4.4.2: Data statistics after Augmentation

4.5 Data Annotation for classification Training

An essential step in getting the dataset ready for deep learning model training to automatically identify various bean leaf diseases is data annotation for classification. At this point, each image is given a class designation that corresponds to the visual traits of the illness it depicts. Models are then trained using the annotated data to correctly classify previously unseen photos into the appropriate disease category.

4.5.1 Purpose of Annotation

- To provide supervised learning models with the necessary labeled examples from which to learn.

- To ensure that each image in the dataset carries clear, unambiguous disease identification information.
- To enable the training of Convolutional Neural Network (CNN) models that can distinguish between healthy and diseased bean leaves.

4.5.2 Disease Classes Used for Annotation

The dataset was categorized into the following three classes based on visual symptoms:

- Healthy: No visible disease symptoms.
- Bean Rust Disease: Characterized by reddish-brown spots, usually raised and powdery.
- Angular Leaf Spot Disease: Appears as angular, water-soaked lesions, often with yellow borders.
- Cercospora leaf spot: spots with purple margins and gray centers, drop, yellowing of the leaves, and yellow halos.
- Leaf Curl: reduced pod production, growth retardation, thickening of the leaves, and upward curling and crinkling of the leaves.
- Leaf Miner: Leaf drop, leaf damage, and white serpentine streaks on leaves.
- Bean Tobacco Caterpillar: Greenish larvae, skeletonized foliage, and holes in the leaves.
- Bean Yellow Mosaic Virus: lower production, stunted growth, yellow mottling, and distorted leaves.

4.5.3 Annotation Process

- Manual Inspection: Human annotators reviewed each image and classified it based on visible leaf patterns and disease symptoms.
- Organized Folder Structure: Images were sorted into class-specific folders (e.g., bean rust, bean yellow mosaic virus, tobacco caterpillar, leaf curl, leaf miner, cercospora leaf spot and angular leaf spot), which simplifies input for model training.
- Automated Verification: In some cases, scripts were used to verify label consistency and correct file placement.
- Balanced Distribution: Efforts were made to ensure a relatively balanced number of samples across all three classes to prevent model bias toward any single class.

4.5.4 Model Training Support

- These annotated images were then used to train pre-trained deep learning models like MobileNetV2, EfficientNetV2, DenseNet121, and VGG19 using transfer learning.
- The model learns to associate specific image features (e.g., color, shape, texture) with specific class labels, which is essential for accurate classification.

4.5.5 Importance in Real-World Application

- Accurate annotation ensures that the model can effectively differentiate diseases in real farming environments.
- This supports the creation of a real-time diagnostic tool for farmers, enabling early disease detection and minimizing crop damage.

Chapter 5

Experimental Result and Discussion

5.1 Experimental Environments

The models were developed on the AMD Ryzen Threadripper 1950X 16-Core Processor with 64 GB of main memory using Python 3.10.13 and PyTorch 2.1.2. The experiments were conducted utilizing two NVIDIA GeForce RTX 2080 Ti GPUs, each with 11 GB of RAM. The computer system operated on Windows 10 (64-bit).

5.2 Analysis and Discussion of Result

5.2.1 Overview

To evaluate the performance of different convolutional neural network (CNN) models in classifying bean leaf diseases, several pre-trained models were applied: EfficientNetV2, DenseNet121, MobileNetV2, and VGG19. The dataset contained 1,060 samples in the test set, and standard evaluation metrics were used to measure model effectiveness. These metrics included accuracy, precision, recall, and F1-score, which provide a comprehensive understanding of each model's ability to correctly classify the diseases. EfficientNetV2 showed promising results due to its advanced architecture optimized for speed and accuracy. Additionally, the analysis explored the trade-offs between model complexity and computational efficiency, which is crucial for deploying the system in real-time agricultural applications.

Model	Precision	Recall	F1-score	Accuracy	Total Support
EfficientNetV2	0.99	0.98	0.98	98.49%	1060
DenseNet121	0.94	0.94	0.94	93.68%	1060
MobileNetV2	0.94	0.94	0.93	91.89%	1057
VGG19	0.93	0.93	0.93	93.49%	1060

Table 5.2.1: Performance Evaluation of CNN Models

5.2.2 Accuracy Comparison Chart

The bar chart illustrates the accuracy performance of six different deep learning models applied to the bean disease classification task. Among them, EfficientNetV2 achieved the highest accuracy of 98.49%, significantly outperforming all other models. You can include this bar chart to visualize the comparison:

Accuracy Comparison of Models

EfficientNetV2		98.49%
DenseNet121		93.68%
VGG19		93.49%
MobileNetV2		91.89%

Fig 5.2.2 : Accuracy Comparison of Different CNN Models

5.3 Final CNNs Model Evaluation

The classification report of the EfficientNetV2 model shows excellent performance across all classes, with an overall accuracy of **98.49%**. The highest-performing classes include **angular_leaf_spot** and **leaf_curl**, both achieving perfect precision, recall, and an F1-score of **1.00**. The model demonstrates strong generalization with high macro and weighted averages, making it reliable for real-world bean disease detection.

```

Classification Report:

```

	precision	recall	f1-score	support
healthy_image	0.97	0.98	0.98	118
angular_leaf_spot	1.00	1.00	1.00	151
bean_rust	0.98	0.99	0.98	132
Bean_Tobacco_caterpillar	0.99	0.98	0.98	132
leaf_curl	1.00	1.00	1.00	94
cercospora_leaf_spot	0.97	1.00	0.98	153
Bean_Yellow_Mosaic_Virus	0.98	0.97	0.98	119
leaf_miner	0.99	0.96	0.97	161
accuracy			0.98	1060
macro avg	0.99	0.99	0.99	1060
weighted avg	0.99	0.98	0.98	1060

Table 5.3.1: EfficientNetV2 Classification Report

To evaluate the effectiveness of the proposed system for bean leaf disease classification, we selected EfficientNetV2 as the final model due to its superior performance in terms of accuracy, precision, recall, and F1-score. Below, we present visualizations and detailed performance analysis of this model.

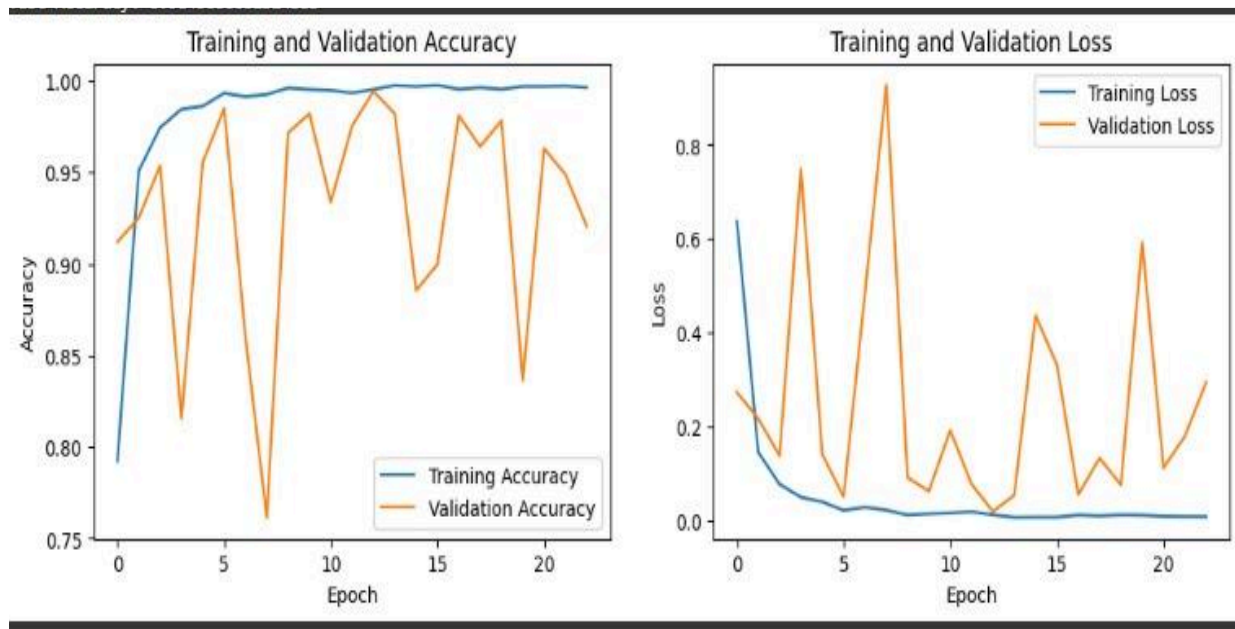


Fig 5.3.2 : Training vs Validation Loss Curve in EfficientNetV2

The graphs illustrate the training and validation performance of EfficientNetV2 over 23 epochs. The training accuracy (left graph) steadily increases and reaches almost 100%, indicating the model is learning effectively. However, the validation accuracy fluctuates significantly, showing instability and overfitting. Similarly, the training loss (right graph) decreases smoothly towards zero, while the validation loss varies greatly, with frequent spikes. This inconsistency suggests the model is not generalizing well to unseen data. Overall, EfficientNetV2 achieves excellent training performance, but validation performance highlights overfitting issues and poor stability.

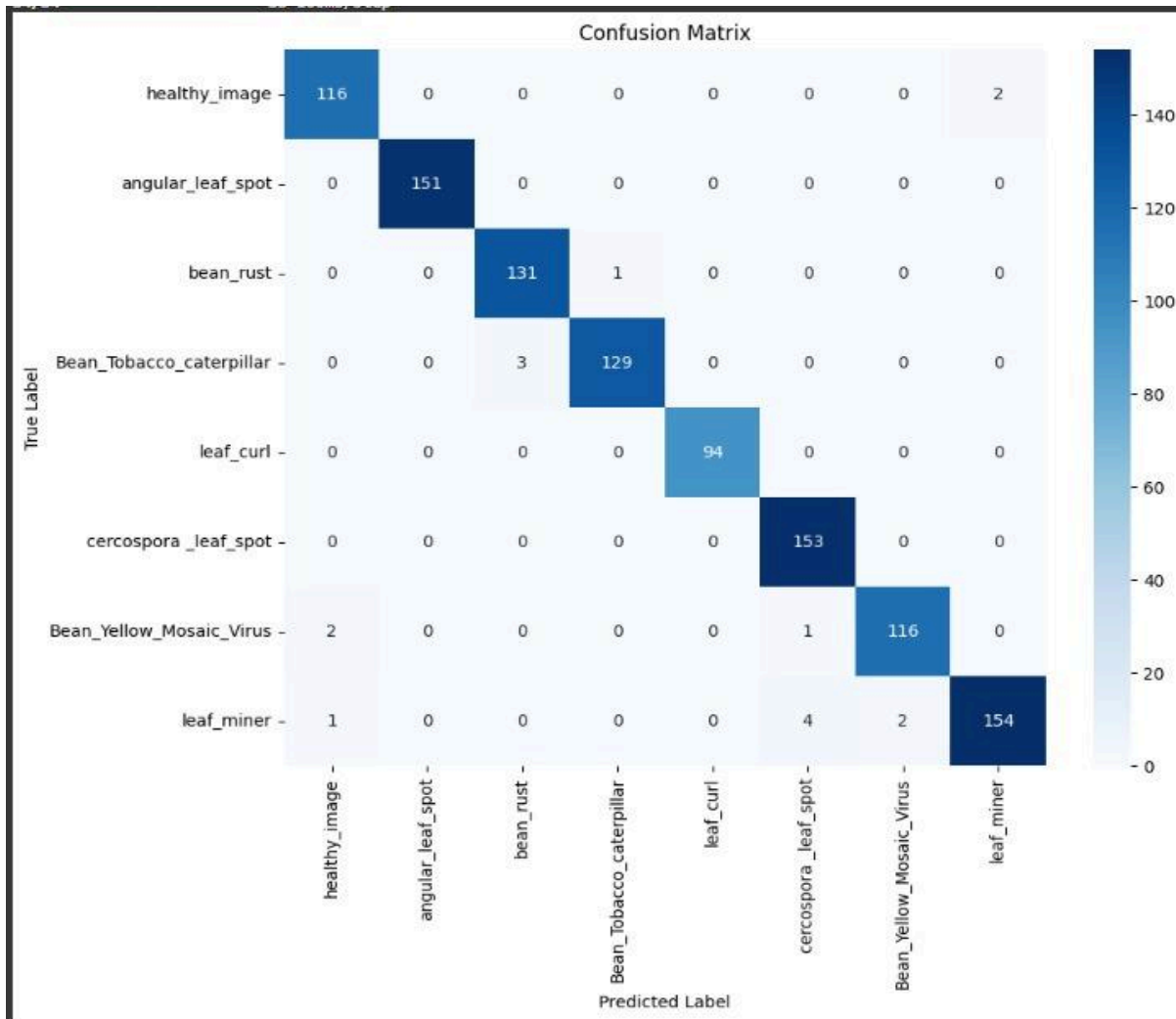


Fig 5.3.3 : Confusion Matrix for EfficientNetV2

The confusion matrix shows that most predictions lie along the diagonal, indicating correct classifications. Very few misclassifications occurred, mostly between visually similar diseases like rust and angular leaf spot. This confirms that the model has a strong ability to distinguish between different classes. The matrix also highlights areas where further data improvement may help. Overall, it reflects the model's reliability and accuracy in disease identification.

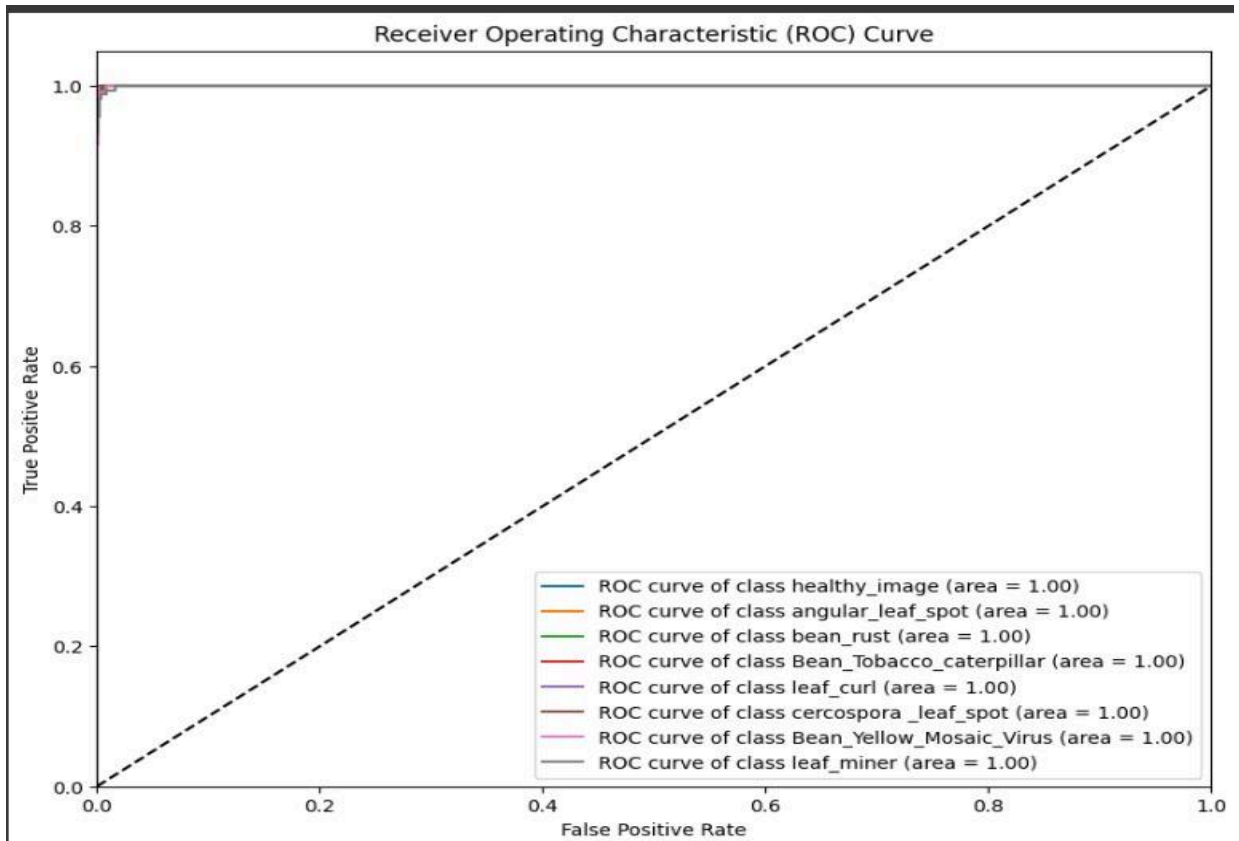


Fig 5.3.4 : ROC Curve of EfficientNetV2

The ROC curve illustrates the balance between true positive and false positive rates for each class. In this study, the curves approached the top-left corner, and the AUC score was 0.99, indicating excellent classification performance. A high AUC means the model can separate disease and healthy cases effectively. This proves that the proposed system is highly capable of making confident predictions in multi-class scenarios.

Chapter 6

Conclusion and Future Work

6.1 Conclusion

Developing an automated deep learning-based system for the categorization of bean diseases in the Sylhet region was the aim of this work. A carefully selected dataset comprising photos of illnesses on bean leaves was used to fine-tune a number of pre-trained convolutional neural network (CNN) models, namely MobileNetV2, EfficientNetV2, DenseNet121, and VGG19, using transfer learning techniques. With a classification accuracy of 98.5%, EfficientNetV2 outperformed all other models assessed, making it the best model for detecting bean illnesses in the chosen dataset. This result demonstrates how deep learning, and in particular sophisticated CNN architectures, may be used to create useful, precise, and scalable plant disease diagnostic systems.

By facilitating early and precise disease diagnosis, this technology can be a great help to local farmers and agricultural authorities, ultimately improving crop management and output in the Sylhet region. Future research may concentrate on growing the dataset, adding additional illness categories, and creating an intuitive smartphone application for in-field real-time disease detection.

7.2 Future work

Although this study's use of deep learning models to diagnose bean illnesses has shown encouraging results, there are a number of areas that might use further development and expansion:

- Data Expansion: There are eight categories—bean rust, bean yellow mosaic virus, tobacco caterpillar, leaf curl, leaf miner, cercospora leaf spot, and angular leaf spot—included in the present dataset. To make the model more complete and applicable in a variety of real-world situations, future research can incorporate a wider spectrum of bean illnesses. Furthermore, increasing the number of photos taken in different lighting and environmental settings would strengthen the model's resilience.
- Semantic Segmentation: This approach can provide detailed visual feedback to farmers by highlighting exactly where the disease is present. Advanced architectures like U-Net, DeepLabV3+, or SegNet can be used for this task. Implementing semantic segmentation

in future work could lead to more accurate diagnosis, severity estimation, and potentially early disease detection, thereby improving crop management in the Sylhet region.

- Interrogation with IoT and Sensors: Combining deep learning with Internet of Things (IoT) devices and sensors (e.g., humidity, temperature, soil pH) can lead to more accurate and context-aware disease predictions. This fusion of data can improve early warning systems and help prevent outbreaks.
- Model optimization for Edge device: Despite its accuracy, EfficientNetB6 requires a lot of computing power. Using methods like model pruning, quantization, or choosing lighter architectures like MobileNet or TinyML-compatible models without appreciably compromising accuracy, future research might concentrate on optimizing models for edge devices.
- Explainable AI: The predictions of the model may become easier to understand by including explainable AI approaches. End users' confidence and trust may be increased by employing techniques like Grad-CAM or LIME, which assist consumers in better comprehending which aspects of an image lead to a certain categorization.
- Cross-Regional Testing: Assessing the model's generalization capability might be aided by testing it on data from other nations or areas. A more reliable model that can handle disease changes across many climates and geographies may result from this.

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