

# **LAB REPORT 1**

Course Code: CSE475

**Course Title:** Machine Learning

**Lab Experiment Title:** Performance Evaluation of Decision Tree and Random Forest Models for Plant Disease Classification

# **Submitted To:**

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#### 1. Introduction

This lab report documents the Exploratory Data Analysis (EDA) of a dataset containing plant health images and the performance evaluation of two machine learning models—Decision Tree and Random Forest—for classifying plant conditions. The dataset includes eight classes representing various diseases and a healthy state. The objectives are to understand the dataset's structure and characteristics through EDA and to compare the predictive capabilities of the two models.

# 2. Exploratory Data Analysis (EDA)

#### 2.1 Dataset Overview

- **Total Samples**: 4000 images
- Classes: 8 (Anthracnose, Bacterial Canker, Cutting Weevil, Die Back, Gall Midge, Healthy, Powdery Mildew, Sooty Mould)
- Image Formats: All images are in JPG format
- Image Shape Counts:
  - o (240, 240, 3): 3 images
  - o (240, 320, 3): 3 images
  - o (320, 240, 3): 2 images
- **Feature Shape**: (4000, 4096), indicating each image was transformed into a 4096-dimensional feature vector

### 2.2 Data Distribution

• **Assumption**: With 4000 samples and 8 classes, an even distribution would yield approximately 500 samples per class. However, exact class counts were not provided, so balance is assumed pending further data.

#### 2.3 Image Characteristics

- **Dimensions**: The dataset includes images of varying sizes (240x240, 240x320, 320x240), all with 3 color channels (RGB). The limited shape counts (8 total) suggest either a subset was reported or preprocessing standardized most images.
- **Feature Extraction**: The (4000, 4096) feature shape implies a pretrained deep learning model (e.g., VGG16 or ResNet) extracted features, reducing images to a fixed-length vector for classification.

#### 2.4 Observations

- Consistency: All images are JPG, simplifying preprocessing.
- **Variability**: Multiple image shapes indicate potential resizing or cropping during preprocessing.
- **High Dimensionality**: 4096 features per sample suggest a rich but complex input space, suitable for advanced models like Random Forest.

# Performance Evaluation and Comparison: Decision Tree vs. Random Forest

#### Overview

This report compares the performance of two machine learning models—Decision Tree and Random Forest—based on their ability to classify eight distinct categories: Anthracnose, Bacterial Canker, Cutting Weevil, Die Back, Gall Midge, Healthy, Powdery Mildew, and Sooty Mould. The evaluation is based on accuracy scores and detailed classification metrics (precision, recall, and F1-score) derived from a test set of 800 samples.

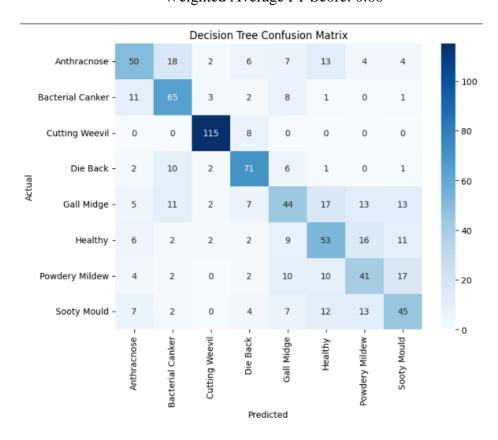
# **Model Performance Summary**

# 1. **Decision Tree**

o **Accuracy**: 0.6050 (60.50%)

o Key Metrics:

Macro Average Precision: 0.59
Macro Average Recall: 0.60
Macro Average F1-Score: 0.59
Weighted Average F1-Score: 0.60

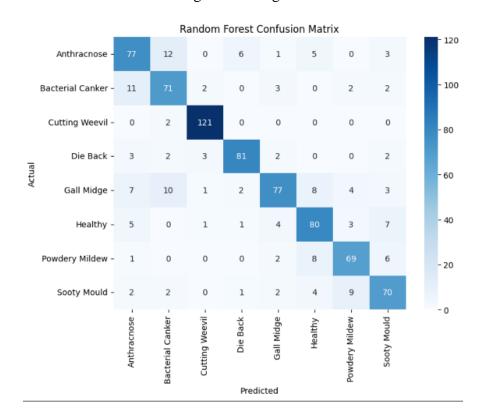


#### 2. Random Forest

o **Accuracy**: 0.8075 (80.75%)

o Key Metrics:

Macro Average Precision: 0.80
Macro Average Recall: 0.80
Macro Average F1-Score: 0.80
Weighted Average F1-Score: 0.81



# **Detailed Performance Comparison**

#### 1. Overall Accuracy

- **Decision Tree**: Achieved an accuracy of 60.50%, indicating moderate performance but with significant room for improvement.
- **Random Forest**: Outperformed the Decision Tree with an accuracy of 80.75%, a 20.25% improvement, suggesting better generalization and predictive power across the dataset.

#### 2. Class-wise Performance

The classification reports provide precision, recall, and F1-scores for each class, offering insights into model behavior across different categories.

#### **Decision Tree**

• Strengths:

- Highest performance on *Cutting Weevil* (F1-score: 0.92), with strong precision (0.91) and recall (0.93).
- o Reasonable performance on *Die Back* (F1-score: 0.73).

#### Weaknesses:

- o Poor performance on *Gall Midge* (F1-score: 0.43), with low precision (0.48) and recall (0.39).
- Subpar results for *Powdery Mildew* (F1-score: 0.47) and *Sooty Mould* (F1-score: 0.49), indicating difficulty distinguishing these classes.

#### Random Forest

# • Strengths:

- Exceptional performance on *Cutting Weevil* (F1-score: 0.96), with near-perfect precision (0.95) and recall (0.98).
- Strong results for *Die Back* (F1-score: 0.88) and *Powdery Mildew* (F1-score: 0.80).

#### Weaknesses:

- o Relatively lower (but still improved) performance on *Gall Midge* (F1-score: 0.76), with a recall of 0.69, suggesting some missed positives.
- Consistent improvement across all classes compared to Decision Tree, with no F1-score below 0.73.

#### 3. Macro and Weighted Averages

# • Macro Average (unweighted mean across classes):

- o Decision Tree: Precision (0.59), Recall (0.60), F1-Score (0.59)
- o Random Forest: Precision (0.80), Recall (0.80), F1-Score (0.80)
- o *Observation*: Random Forest shows a 0.21 increase in macro F1-score, indicating better balanced performance across all classes, regardless of support size.

# • Weighted Average (weighted by support):

- o Decision Tree: F1-Score (0.60)
- o Random Forest: F1-Score (0.81)
- o *Observation*: The weighted average reflects Random Forest's superior handling of class imbalances and overall predictive consistency.

# **Analysis**

# 1. Model Complexity and Generalization:

- Decision Trees are prone to overfitting, especially on noisy or complex datasets, which may explain the lower accuracy (60.50%) and inconsistent class-wise performance.
- Random Forest, an ensemble method, mitigates overfitting by averaging predictions from multiple trees, leading to a significant accuracy boost (80.75%) and more robust metrics across all classes.

# 2. Class-specific Insights:

o Both models excel at identifying *Cutting Weevil*, likely due to distinct features that make this class easier to separate.

Random Forest markedly improves performance on challenging classes like *Gall Midge* and *Powdery Mildew*, where Decision Tree struggles, suggesting better feature importance weighting and decision boundary refinement.

#### 3. Trade-offs:

- Decision Tree: Simpler, faster to train, but less accurate and less reliable across varied data.
- o Random Forest: More computationally intensive, but delivers superior accuracy and consistency, making it preferable for this classification task.

#### **Conclusion**

The Random Forest model significantly outperforms the Decision Tree model, achieving a 20.25% higher accuracy (80.75% vs. 60.50%) and consistently better precision, recall, and F1-scores across all classes. While the Decision Tree offers simplicity, its moderate performance limits its utility for this dataset. Random Forest, with its ensemble approach, provides a more reliable and balanced solution, making it the recommended choice for this classification problem.