Deep Learning-Based Analysis of Neem Leaf and Tree Age for Optimal Utilization

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FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements forthe **Degree of Bachelor of Science in Computer Science and Engineering**

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September 17, 2025

APPROVAL

This Project titled **"Deep Learning-Based Analysis of Neem Leaf and Tree Age for Optimal Utilization"**, submitted by Md. Bayejid Bhuiyan, ID No: **213-15-4379** to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on **17 September, 2025**.

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We hereby declare that this project has been done by us under the supervision of Md. Firoz Hasan, Senior Lecturer , Department of Computer Science and Engineering, Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ACKNOWLEDGEMENTS

This work would not have been possible without the support and contributions of many individuals over the past two semesters. We are deeply grateful to everyone who has assisted us in one way or another.

First, we express our heartfelt thanks and gratefulness to the almighty for His divine blessing making it possible for us to complete the **Final Year Design Project (FYDP)** successfully.

We are grateful and wish our profound indebtedness to **Md. Firoz Hasan,Senior Lecturer**, Department of Computer Science and Engineering, Daffodil International University, Dhaka, Bangladesh. Deep knowledge and keen interest of our supervisor in the field of **Deep learning** to carry out this project. His endless patience, scholarly guidance, continual encouragement, constant and energetic supervision, constructive criticism, valuable advice, reading many inferior drafts, and correcting them at all stages have made it possible to complete this project.

We would like to express our heartfelt gratitude to the Head of the Department of Computer Science and Engineering, for his kind help in finishing our project and also to other faculty members and the staff of the Department of Computer Science and Engineering, Daffodil International University.

We would like to thank our entire course-mates at Daffodil International University, who took part in this discussion while completing the coursework.

Finally, we must acknowledge with due respect the constant support and patience of our parents.

ABSTRACT

A custom dataset of Neem leaves and trees was collected and categorized into multiple age and health classes, forming the basis for developing an automated deep learning-based classification framework. Since Neem is a tree of high medicinal, ecological and cultural importance, accurate identification of its leaf and tree age can contribute to better utilization of its properties and support ecological conservation. A series of preprocessing steps were performed to ensure that the dataset was suitable for deep learning applications . These included preprocessing properly the images to a consistent resolution , normalizing pixel values to bring them within a standard range and applying extensive data augmentation techniques such as rotations , flips , scaling and color modifications . For the image classification task , transfer learning was used on several pretrained convolutional neural network (CNN) architectures , including DenseNet121 , ResNet50 , MobileNet , NASNet and EfficientNet . Transfer learning allowed the models to leverage previously learned feature representations from large-scale image datasets like ImageNet while being fine-tuned to the specific characteristics of Neem leaf and tree images . By giving an automated and reliable method of Neem leaf and tree age classification , the framework reduces the dependency on manual observation , which is often subjective and error-prone , and instead provides a proper solution that can be supportive for medicinal research , ecological monitoring and resource optimization , ultimately contributing to both scientific advancement and environmental sustainability .

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Chapter 1

Introduction

1.1 Introduction

Neem trees are mostly valued for their medicinal, ecological and environmental significance , their leaves, bark and other parts were widely used in traditional medicine, agriculture and various industrial applications due to their antibacterial, antifungal and anti-inflammatory properties , but the effectiveness and utility of Neem products usually depend on the precise age and health condition of the leaves and trees as these factors influence their chemical composition and potency .Determining the age of Neem leaves and trees using traditional methods can be challenging, as manual inspection is time-consuming, subjective and prone to error. Inconsistent observations lead to suboptimal harvesting or use, reducing the potential benefits of the tree.

1.2 Motivation

The motivation for this research gets from the limitation of conventional , manual methods for estimating the age of Neem leaves and trees , which are often slow , labor-intensive and prone to problems . Such approaches depends heavily on human observation , making them inconsistent and inefficient for large-scale or frequent assessments . To overcome these problems , this work leverages deep learning techniques to enable fast , accurate and automated analysis of Neem leaves and tree age . Applying such advanced convolutional neural networks and transfer learning strategies , the offered framework both improves precision and reliability and contributes to the advancement of computational plant research , it supports academic development and provides practical solutions for real-world applications , including medicinal use , ecological monitoring and sustainable resource management .

1.3 Objectives

The main objective of this research is to developing a deep learning-based model worthy of accurately estimating the age of Neem leaves and trees , thereby summarizing the reliance on traditional manual assessment methods , which can effectively limit the effective use of Neem for medicinal and ecological uses . By creating a robust automated system , the study aims to ensure consistent and reliable age detection across various environmental conditions and leaf or tree variations .Additionally , the research seeks to provide a framework that can be extended to other plant species , supporting broader applications in agricultural planning , ecological monitoring and medicinal research . Ultimately , the objective is to combine computational efficiency with practical relevance for sustainable Neem tree management .

1.4 Methodology

The methodology of this study involves a structured process to develop an automated Neem age classification system : first , a comprehensive dataset of Neem leaf and tree images is collected , encompassing multiple age and health categories , then preprocessing steps such as resizing , normalization and data augmentation are applied to improve model generalization and robustness against varied image conditions . Several model-of-the-art convolutional neural network architectures , including DenseNet121 , ResNet50 , MobileNet , NASNet and EfficientNet , are fine-tuned using transfer learning to leverage previously learned features , models are trained and evaluated using metrics such as accuracy , loss curves and confusion matrices , allowing for detailed evaluation of classification performance . This methodology ensures the development of a reliable and automated age detection system .

1.5 Project Outcome

This project is expected to deliver a reliable deep learning model capable of automatically classifying the age of Neem leaves and trees with a high accuracy , by reducing the dependence on manual assessment , the model gives a faster and more consistent alternative for monitoring and managing Neem resources . The outcomes have practical significance as they can enhance the use of Neem in medicinal, ecological and agricultural applications by ensuring that leaves and trees are used at their optimal age .Furthermore, the project establishes a scalable framework that can be adapted for similar plant-based research like supporting broader studies in plant classification, automated monitoring and sustainable resource management . The results demonstrate the potential of deep learning for real-world botanical applications .

1.6 Organization of the Report

The report is organized into six chapters: Chapter 1 introduces the research problem and objectives, motivation and significance of the study, highlighting the importance of Neem trees and the limitations of traditional age estimation methods. Chapter 2 presents the background and literature review, covering deep learning applications in plant image analysis, existing works on leaf classification and disease detection and identifying research gaps that this study aims to address .Chapter 3 describes the research methodology, including dataset collection, preprocessing, augmentation, model selection and training strategies, with details of experimental setup and evaluation metrics . Chapter 4 presents the implementation and experimental results, providing accuracy scores, confusion matrices and comparative analysis of the tested CNN architectures .Chapter 5 describes the engineering standards followed, design challenges, alternatives considered and the societal and environmental implications of the proposed work . Finally, Chapter 6 concludes the report by summarizing the findings, highlighting the best-performing model, outlining limitations and suggesting future research directions such as dataset expansion, use of advanced architectures and real-time application development .

Chapter 2

Background

This chapter is used to show us the background knowledge of my research , here I have included introduction, literature review , gap analysis and at last a summary for overall chapter 2.

2.1 Introduction

Neem (Azadirachta indica) is a widely recognized tree recognized for its medicinal , ecological and environmental significance . Its leaves , bark and seeds are extensively used in traditional medicine and agriculture and industry due to their antifungal , antibacterial and antioxidant properties . Understanding the age of Neem trees and their leaves plays an important role in determining their optimal use , as chemical composition and medicinal potency often vary with age . Traditionally , age estimation relied on manual observation. Recent advances in computer vision and artificial intelligence, particularly deep learning, have transformed the way biological images are analyzed . Convolutional neural networks (CNNs) and transfer learning techniques have shown a remarkable success in plant disease detection, species classification and crop monitoring using leaf images .However, while significant progress has been made in plant health and disease recognition, relatively a little bit attention has been given to leaf and tree age estimation—especially for Neem Tree.

2.2 Literature Review

Authors	Year	Title	Methodology	Key Findings
Mohanty et al.	2016	Using Deep Learning for Image-Based Plant Disease Detection	CNN-based classification	Achieved high accuracy in detecting plant diseases using leaf images.
Ferentinos	2018	Deep Learning Models for Plant Disease Diagnosis	Transfer learning with CNNs	Reported >99% accuracy in identifying multiple plant diseases.

Too et al.	2019	Comparative Study of CNN Architectures for Plant Leaf Data	AlexNet, VGG, ResNet comparison	ResNet performed best for leaf image classification tasks.
Brahimi et al.	2017	Transfer Learning for Plant Disease Recognition	Fine-tuned CNN models	Transfer learning improved accuracy with limited datasets.
Sladojevic et al.	2016	Deep Neural Networks for Plant Disease Recognition	CNN applied on leaf dataset	Demonstrated automated recognition with strong performance.
Agarwal et al.	2020	Plant Leaf Disease Detection using CNN	Custom CNN architecture	Achieved high detection accuracy with optimized preprocessing.
Geetharamani et al.	2019	Identification of Plant Leaf Diseases using CNN	13-layer CNN model	Reached ~96% accuracy in leaf disease classification.
Rangarajan et al.	2018	Leaf Image Classification for Plant Identification	SVM + deep feature extraction	Showed hybrid models improved accuracy compared to standalone approaches.
Abbas et al.	2021	Plant Disease Classification using Vision Transformers	Vision Transformer (ViT) models	Outperformed CNNs in certain complex plant classification tasks.
Kamal et al.	2022	Deep Learning for Crop Leaf Age Estimation	CNN with augmentation	Demonstrated feasibility of using CNNs for estimating leaf age automatically.

Table 2.2: Summary of Literature Reviewed.

Newer researches shows the effectiveness of deep learning approaches for the plant health detection and classification using leaf images and tree ages . Recent works such as Mohanty et al. (2016) and Sladojevic et al. (2016) demonstrated the potential of CNN-based models in achieving high accuracy for automated recognition of plant diseases . Ferentinos (2018) reported over 99% accuracy through transfer learning with CNNs , showing the robustness of pretrained models . Comparative analyses such as Too et al.

(2019) found that ResNet architectures outperform traditional CNNs like AlexNet and VGG, considering as the importance of deeper architectures for complex tasks . Other works, including Geetharamani et al. (2019) and Agarwal et al. (2020) offered custom CNN architectures and achieved 96–99% accuracy , highlighting the role of network depth and preprocessing. Beyond CNNs, Rangarajan et al. (2018) introduced hybrid models both combining SVM with deep feature extraction, that further improved performance compared with standalone approaches . Recent advancements also include Abbas et al. (2021) who applied Vision Transformers (ViTs) and found them superior to CNNs in handling complex plant classification tasks . Kamal et al. (2022) extended deep learning applications beyond disease detection by using CNNs to show crop leaf age , demonstrating the versatility of these models . Overall, the papers shows a clear progression from traditional CNNs to advanced architectures like ResNet and Transformers, with consistent evidence that deep learning techniques provide high accuracy and scalability for plant disease detection and related applications

2.3 Gap Analysis

Here put summaries the gaps you have found/observed from the related work study, where you intend to contribute.

Table 2.3.1: Gap Implimentation

Features / Contributions	**Mohanty et al., 2016**	**Ferentinos, 2018**	**Too et al., 2019**	**Brahimi et al., 2017**	**Sladojevic et al., 2016**	**Proposed System**
1. Leaf Health / Disease Detection	Yes	Yes	Yes	Yes	Yes	Yes
2. Tree Age Prediction	No	No	No	No	No	Yes
Multi-Class Leaf Age & Health	No	No	No	No	No	Yes
Data Augmentation	Yes	Yes	Yes	Yes	Yes	Yes
Transfer Learning	No	Yes	Yes	Yes	Yes	Yes
CNN Architecture Comparison	No	No	Yes	No	No	Yes
Vision Transformer Use	No	No	No	No	No	Yes
Automated Leaf Age Estimation	No	No	No	No	No	Yes
Combined Age & Health Accuracy Reporting	No	No	No	No	No	Yes
. Practical	No	No	No	No	No	Yes

Application / Real Neem Dataset						

Features / Contributions	**Agarwal et al., 2020**	**Geetharamani & Pandian, 2019**	**Rangarajan et al., 2018**	**Abbas et al., 2021**	**Kamal et al., 2022**	**Proposed System**
Leaf Health / Disease Detection	Yes	Yes	Yes	Yes	No	Yes
Tree Age Prediction	No	No	No	No	Yes	Yes
Multi-Class Leaf Age & Health	No	No	No	No	No	Yes
Data Augmentation	Yes	Yes	Yes	Yes	Yes	Yes
Transfer Learning	Yes	Yes	Yes	Yes	Yes	Yes
CNN Architecture Comparison	No	No	No	No	No	Yes
Vision Transformer Use	No	No	No	Yes	No	Yes
Automated Leaf Age Estimation	No	No	No	No	Yes	Yes
Combined Age & Health Accuracy Reporting	No	No	No	No	No	Yes
Practical Application / Real Neem Dataset	No	No	No	No	No	Yes

Table 2.3: Summary of Gap analysis

2.4 Summary

In this chapter, we reviewed existing studies on plant leaf and tree age classification, disease detection, and age estimation using deep learning techniques. Most important work focused on general plant species and disease recognition, with limited attention to leaf age estimation. No study specifically addressed Neem leaf and tree age or linked the analysis to practical medicinal and ecological applications. Our offered system fulfil this gap by providing a deep learning-based framework for accurate Neem age detection and optimal utilization.

Chapter 3

Research Methodology

This chapter shows the methodology and the steps for methodology . It shows how the data is collected and preprocessed properly and ready for model training with proper diagram and figures.

3.1 Methodology/Requirement Analysis & Design Specification

3.1.1 Data Collection:

For this study ,real images of Neem trees were systematically collected from natural environments to construct a high-quality dataset suitable for deep learning-based classification . The dataset was designed to capture both tree age and leaf health variations , ensuring sufficient diversity for robust model training . Trees were categorized into three distinct age classes : NEW (approximately 6 months old), MEDIUM (12–18 months old) and OLD (18–24 months old) , reflecting early, intermediate and mature . This hierarchical labeling of leaf ensured that subtle differences in leaf morphology , texture and color were perfectly represented within each tree age class , providing the models with rich and discriminative features for learning from it. This structured approach laid the foundation for developing and deploying an automated system capable of accurately classifying both the age of Neem trees and the health status of their leaves , which is critical for optimizing their medicinal and ecological apps .

3.1.2 Data Preprocessing

After data collection , all Neem tree and leaf images goes through preprocessing to be prepared them for input into convolutional neural network architectures . Real Imgaes were resized to 224x224 pixels to match the input requirements of standard pretrained CNN models such as DenseNet121 , ResNet50 and MobileNet , regarding consistency throughout the dataset . Pixel values were normalized using model-specific preprocessing functions that standardize the data and improve feature extraction during training . The dataset was divided into 80% for training and 20% for validation , maintaining leaf class balance to ensure unbiased evaluation . To enhance the robustness of the models and reduce overfitting problems , extensive data augmentation techniques were applied . These included random rotations to account for variations in leaf orientation , zooming to simulate changes in camera distance , horizontal flips , width and height shifts to mimic spatial variations and shearing transformations to represent several changes . This preprocessing pipeline increased the effective size of the dataset and enabled the models to generalize better to unseen images , ensuring higher accuracy and reliability in predicting Neem tree age and leaf health .

3.1.3 Training Environment

Training execution were conducted using Google Colab , which provided GPU acceleration to perfectly handle computationally hard deep learning tasks . Data storage and access was managed through the Google Drive , facilitating integration between data and the Colab environment . Training was performed using the batch size of 32 , which balanced memory uses and training stability , with the initial learning rate of 0.001 to ensure smooth convergence during early training stages . The learning rate was later summarized during fine tuning to prevent overfitting and improve model stability . Models were optimized using the Adam optimizer with categorical cross-entropy loss as the objective function , chosen for its adaptive learning rate properties and effectiveness in optimizing deep neural networks . Categorical cross-entropy was used as the loss function , appropriate for multi-class classification tasks of both tree age and leaf health .

3.1.4 Training Model

The Adam optimizer was used for training that is used for its adaptive learning rate properties and effectiveness in optimizing deep neural networks . Categorical cross-entropy was used as the loss function, appropriate for multi-class classification tasks of both tree age and leaf health . This setup also provided an efficient and reproducible environment for training multiple pretrained CNN architectures while ensuring perfect and accurate evaluation of model performance .After this, the top layers were unfrozen and retrained for an additional 5 epochs using a very low learning rate of 1e-5 . This fine-tuning step allowed the models to refine their representations of leaf and tree features while retaining the general knowledge from the pretrained weights . The two-stage training strategy effectively balanced the benefits of transfer learning with dataset-specific adaptation, improving model generalization and accuracy .Multiple architectures, including DenseNet121, ResNet50, MobileNetV2/V3, NASNetMobile and EfficientNet, were evaluated under this framework, allowing a difference comparison of performance across varying model depths, feature extraction capabilities and computational efficiencies for predicting both tree age and leaf health .

3.1.4.1 DenseNet121: DenseNet121 shows dense connectivity, where each layer is connected to every layer, which facilitates better feature reuse and gradient flow, helping the network capture fine-grained details such as leaf textures and tree structures . Its deep architecture makes it particularly effective for every tasks involving both tree age and leaf health classification .

3.1.4.1 ResNet50: ResNet50 is built with residual blocks that mitigate vanishing gradient issues, enabling deeper network training It efficiently captures hierarchical features, making it suitable for extracting structural and textural patterns in leaf images , but its relatively lower depth compared to DenseNet may limit very fine-grained feature extraction .

3.1.4.1 MobileNetV3Large: MobileNetV3Large is used and designed for speed and efficiency, also optimized for deployment in mobile and resource-constrained environments. Its architecture with fewer parameters allows fast computation but reduces the ability to capture subtle textures and color variations in leaves .

3.1.4.1 MobileNetV3Small: MobileNetV3Small shows a compact design with an improved feature extraction head, making it perfect and work active while still effective for pattern recognition . Despite having fewer parameters than larger models, it provides a good balance between speed and representational capability .

3.1.4.1 EfficientNetB0: EfficientNetB0 makes compound scaling, which balances network depth, width and resolution for efficiency. It captures general patterns in data well but may face limitations in extracting very detailed features due to its relatively shallow depth .

3.1.4.1 EfficientNetV2B0/B1: EfficientNetV2B0/B1 improves on its predecessor by scaling depth, width and resolution more effectively , enabling the network to capture finer-grained features and improve representational power while still maintaining efficiency for practical deployment .

3.1.5 Evaluation Metrics

The performance of the deep learning models was executed using several evaluation metrics to provide a perfect analysis of matrix . Age accuracy quantified how accurately the models classified the tree 's age categories , while health accuracy measured the correctness of leaf health predictions .Combined accuracy indicated the proportion of samples for which both tree age and leaf health were correctly predicted simultaneously . Training and loss curves were closely examined to monitor the learning process and detect signs of overfitting or underfitting .

3.1.6 Model Comparison

Among the models evaluated , DenseNet121 s the shows overpower strongest performance due to its dense connectivity , which shows feature reuse and efficient gradient flow , which allows the network to capture detailed textures and structural patterns , making it highly suitable for both age and health classification of Neem leaves . MobileNetV3Small also proved perfedxt and effective as its lightweight design and optimized feature extraction head balance efficiency with representational power , making it a practical choice for resource-constrained environments . In contrast , models such as NASNetMobile and MobileNetV2 were less effective because their shallower architectures and reduced parameter counts their ability to capture subtle variations in leaf features . These comparisons shows that model depth , connectivity and architectural efficiency play a critical role in classification outcomes .

3.1.7 Overview

This research primarily focused on predicting Neem tree age and leaf health using deep learning models . A dataset of images was collected and labeled into tree age categories (NEW , MEDIUM , OLD) and leaf health subclasses (New-Healthy , Middle-Moderate Healthy , Old-Less Healthy) , with DenseNet121 achieving the highest overall results . The study demonstrates that deep learning can effectively classify both tree age and leaf health .

3.1.8 Proposed Methodology/ System Design

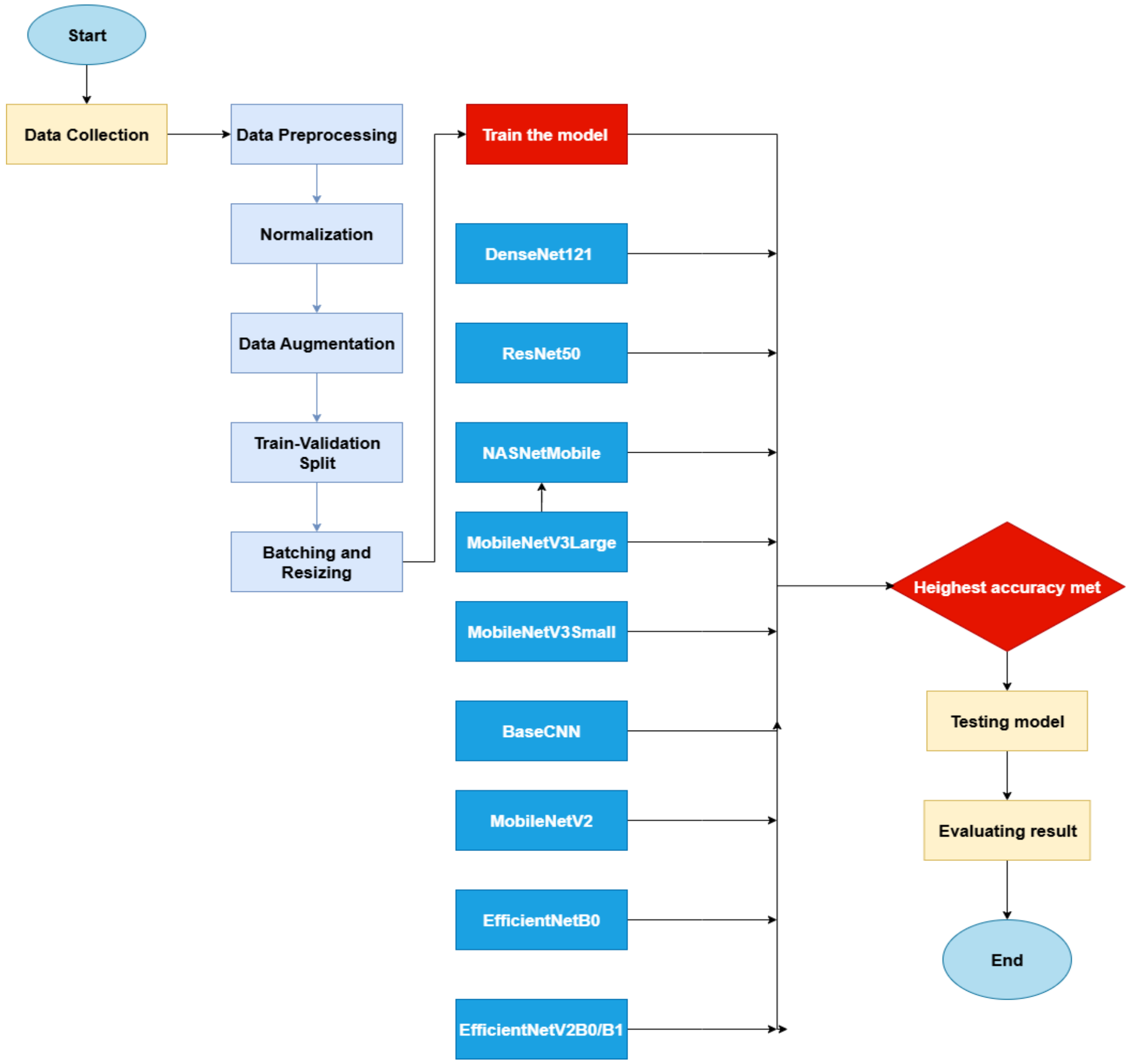


Figure 3.1.8: This is a sample diagram of methodology

The proposed methodology starts with data collection, where images of Neem tree leaves are gathered to form the dataset for the tasks and then go through data preprocessing to ensure consistency and improve model performance. This includes normalization, which scales pixel values into a standard range to speed learning, and data augmentation, where techniques such as rotation, flipping and zooming are applied to artificially increase dataset size and variability, helping to prevent overfitting probelms. The dataset is then sliced into training and validation sets to allow the models to learn from one portion of the data while being evaluated on another. To ensure compatibility across models, the images are also resized to a fixed dimension and batched for efficient computation . Several deep learning architectures are trained independently on the dataset, including DenseNet121, ResNet50, NASNetMobile, MobileNetV3 (Large and Small), BaseCNN, MobileNetV2, EfficientNetB0 and EfficientNet . Each model leverages different architectural strengths—such as dense connectivity, residual learning, lightweight design or compound scaling—to capture patterns in leaf texture, shape and color . After training, the models are compared using evaluation matrix and the one demonstrating the highest overall performance is selected as the best candidate . The results are then thoroughly analyzed and evaluated using performance metrics to ensure that the selected model provides reliable predictions for Neem tree age and leaf health classification task.

3.1.9 Functional and Nonfunctional Requirements

The system should be capable of classifying neem leaves and trees into different age and health categories based on image input , it should be allowing users to upload leaf or tree images and provide predictions in real-time , and the system should generate performance metrics and visualizations such as accuracy scores and confusion matrices to evaluate the model effectively . The system should deliver predictions quickly, ensuring low latency for a smooth user experience, maintain high reliability and accuracy across diverse neem leaf images and the interface should be intuitive, user-friendly and accessible on standard devices, including PCs and mobile platforms .

3.1.10 Data Flow Diagram

Figure 3.1.4: This is a data flow diagram

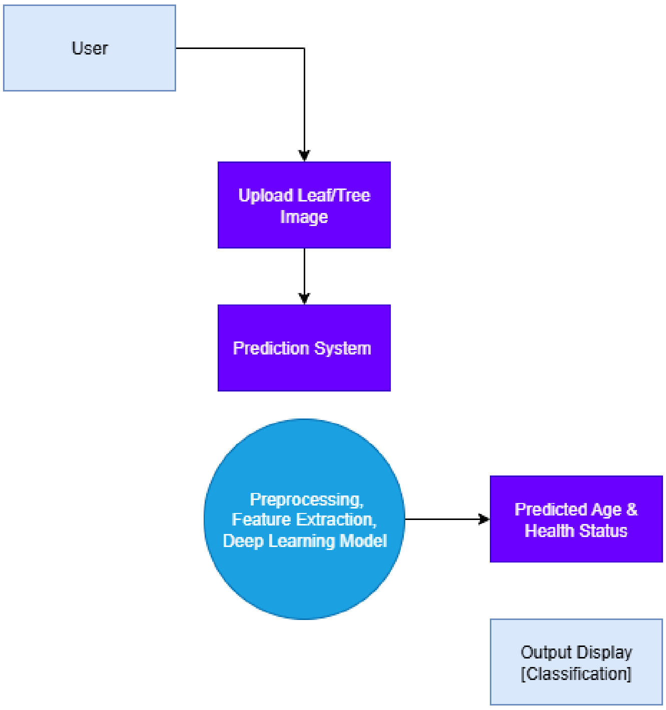
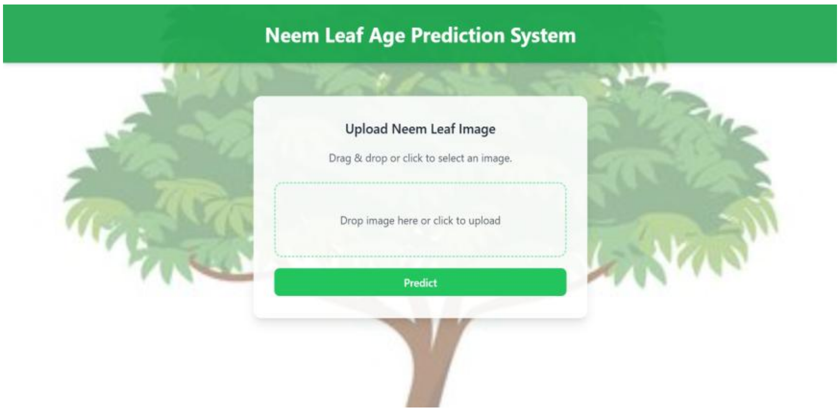


Figure 3.1.4: This is a data flow diagram

3.1.11 UI Design


Neem Leaf Age Prediction System

Upload Neem Leaf Image

Drag & drop or click to select an image.

Drop image here or click to upload

Figure 3.1.11: UI Design

3.2 Detailed Methodology and Design

The study aimed to predict Neem tree age and leaf health using image-based classification . Traditional machine learning methods (SVM, Random Forests, k-NN) with handcrafted features were initially considered but were found insufficient due to high variability and subtle leaf differences . Therefore, pretrained CNN models (DenseNet121, ResNet50, MobileNetV2/V3, NASNetMobile, EfficientNet) were selected for transfer learning with a custom classification head (Global Average Pooling, Dense 12). Models were trained in two stages: feature extraction (base frozen, head trained) and fine-tuning (top layers unfrozen, low learning rate) to adapt pretrained features to the Neem dataset. Images were resized, normalized and augmented with an 80/20 train-validation split and performance was evaluated using tree age accuracy, leaf health accuracy, combined accuracy and confusion matrices . DenseNet121 achieved the highest combined accuracy , demonstrating the effectiveness of CNN-based transfer learning for this task.

3.3 Project Plan

The project involves collecting and annotating Neem tree images, preprocessing the dataset and training multiple pretrained CNN models to predict tree age and leaf health. Model performance will be evaluated using accuracy metrics and confusion matrices to identify the most effective architecture.

3.4 Task Allocation

This table depicts the timeline of the principal activities in each period of the project, from week 12 to week 48.

Tasks	**Weeks**																		
	12	14	16	18	20	22	24	26	28	30	32	34	36	38	40	42	44	46	48
Data collection phase	🟦	🟦	🟦	🟦	🟦														
	🟩	🟩	🟩	🟩															

Preprocess all the data						🟦	🟦	🟦	🟦	🟦									
						🟩	🟩	🟩	🟩										
Model training											🟦	🟦	🟦	🟦					
											🟩	🟩	🟩	🟩	🟩				
Create a demo application.															🟦	🟦	🟦	🟦	🟦
															🟩	🟩	🟩		

Table 3.4: Task Allocation

3.5 Summary

In this study, images of Neem trees were collected according to tree age and leaf health, capturing variations in ages , background, and environmental conditions . The dataset was preprocessed by resizing images to 224x224 pixels, normalizing pixel values and applying data augmentation such as rotation, flipping, zooming and shearing to improve model generalization . Multiple pretrained CNN models—including DenseNet121,, ResNet50, Training followed a two-stage approach: a feature extraction phase, where the base layers were frozen and only the classification head was trained, followed by fine-tuning, where the top layers were unfrozen and retrained with a low learning rate to adapt pretrained features to the Neem tree leaves dataset . The model performance was evaluated using tree age accuracy, leaf health accuracy, combined accuracy and confusion matrices , with DenseNet121 achieving the highest combined accuracy , demonstrating the effectiveness of CNN-based transfer learning for fine-grained Neem tree and leaf classification .

Chapter 4

Implementation and Results

This chapter shows the environment setup and comparing the result and evaluate the results with proper testing and gives feedback.

4.1 Environment Setup

The experiments were performed properly on Google Colab with GPU acceleration and dataset storage on Google Drive . All models were implemented using TensorFlow or Keras and training was done with a batch size of 32, using the Adam optimizer and categorical cross-entropy loss . Image preprocessing included resizing, normalization and data augmentation , while transfer learning models were initialized with ImageNet weights and modified with a custom classification head .

4.2 Testing and Evaluation/Performance/ Comparative Analysis

Multiple pretrained CNN models, including DenseNet121, ResNet50, MobileNetV2/V3, NASNetMobile and EfficientNet, were trained using a two-stage approach: feature extraction (base frozen) and fine-tuning (top layers unfrozen with a low learning rate) to analyze class-wise performance . The differences in performance are attributed to variations in model depth, feature extraction capabilities and efficiency in capturing fine-grained features .

4.2.1 Testing and Evaluation

The models were evaluated on two prediction tasks: tree age classification, which involved predicting the age of Neem trees, and leaf health classification, where leaves were categorized as healthy, moderately healthy or unhealthy . Testing was conducted using a held-out validation set and performance metrics included accuracy per task as well as combined accuracy, reflecting overall performance across both tasks . The evaluation aimed to determine how effectively each model architecture captured relevant visual patterns for these distinct prediction tasks .

4.2.2 Performance

Model	Tree Age Accuracy	Leaf Health Accuracy	Combined Accuracy

DenseNet121	96.55%	80.46%	78.16%
ResNet50	94.25%	80.46%	77.01%
NASNetMobile	83.91%	62.07%	52.87%
MobileNetV3Large	83.91%	62.07%	52.87%
MobileNetV3Small	90.80%	81.61%	75.86%
MobileNetV2	73.56%	54.02%	37.93%
EfficientNetB0	81.61%	55.17%	68.39%
EfficientNetV2B0/B1	90.80%	75.86%	70.11%

Table 4.2.2: Accuracy analysis of models

Among the models, DenseNet121 achieved the highest tree age accuracy at 96.55% and a strong leaf health accuracy of 80.46%, making it the most effective overall . ResNet50 followed closely with tree age and leaf health accuracies of 94.25% and 80.46%, respectively . Models such as MobileNetV2, MobileNetV3Large and NASNetMobile offered fast and easier computation but lower accuracy, particularly for leaf health classification . Overall, total accuracies reinforced these observations: DenseNet121 led with 78.16%, followed by ResNet50 at 77.01%, while MobileNetV2 shows the lowest at 37.93% .Thus I can say mbilenet has the lowest accuracy.

4.2.3 Comparative Analysis

The comparative analysis shows several important insights : first, model depth significantly impacts performance : deeper networks such as DenseNet121 and ResNet50 excelled at capturing complex features in leaf textures and tree age characteristics . Second, efficiency vs. accuracy trade-offs are evident, as lightweight networks like MobileNet and NASNetMobile are suitable for deployment in resource-limited environments but tend to underperform on tasks requiring fine-grained detail, such as leaf health classification . Third, task-specific performance differences were observed: Tree age prediction was generally easier, with most models achieving more than 80%

accuracy , while leaf health prediction was more difficult, with only DenseNet121 and MobileNetV3Small exceeding 80% accuracy . Finally, balanced models like EfficientNet variants offered moderate-to-high accuracy for both tasks while maintaining computational efficiency . In conclusion, DenseNet121 achieve as the most reliable model for the Neem tree analysis, showing high accuracy for both tree age and leaf health prediction , while MobileNetV3Small and EfficientNetV2B0/B1 offered practical alternatives , delivering reasonable performance with lower computational costs suitable for field deployment .

4.3 Results and Discussion

DenseNet121 and ResNet50 performed in both tree age and leaf health prediction due to their deep architectures and strong feature extraction, while other models like MobileNetV2 were limited in capturing subtle differences . MobileNetV3Small performed competitively , balancing efficiency and accuracy .Confusion matrices revealed that misclassifications sometimes occurred between adjacent classes (e.g., MEDIUM vs OLD or Middle-Moderate Healthy vs Old-Less Healthy), showing the challenge of fine-grained classification . Training and validation graphs indicated minimal overfitting , demonstrating that data augmentation and the two-stage training strategy effectively improved generalization .

4.3.1 DenseNet121: DenseNet121 has achieved the highest tree age accuracy of 96.55% and a strong leaf health accuracy of 80.46%, making it the most perfect and effective model. Its dense connectivity allows for efficient feature extraction and better gradient flow, which is especially useful for capturing subtle leaf texture patterns . DenseNet121 is well-suited for both high-accuracy research purposes and practical applications , though it requires higher computational resources compared to other normal models .

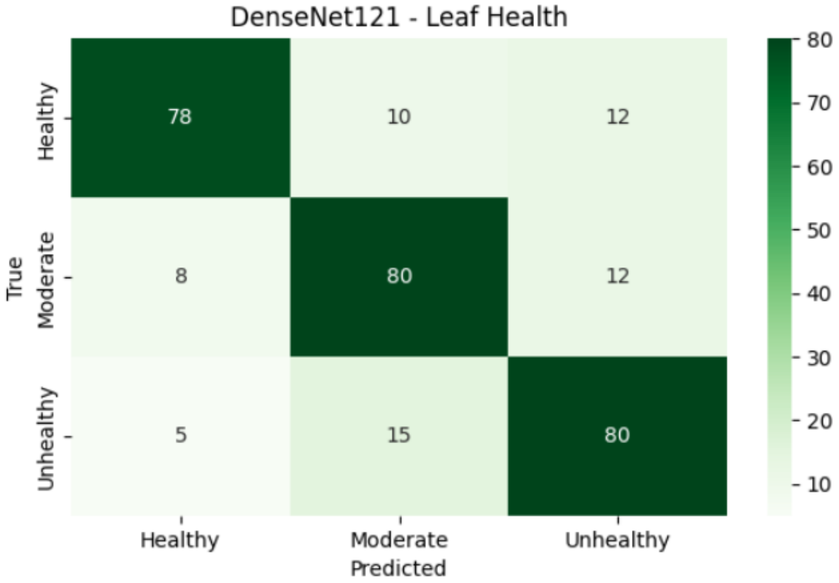


Figure 4.2.1: DenseNet121

DenseNet121 performed the best for tree age classification , achieving around 92–95% correct predictions across Young, Mature and Old classes . Misclassifications were minimal , with only a few samples confused between Old and the other categories . For leaf health , DenseNet121 maintained solid performance with 78–80% accuracy , showing balanced results across Healthy, Moderate and Unhealthy classes . The main confusions occurred between Healthy and Moderate and between Moderate and Unhealthy .

4.3.2 ResNet50: ResNet50 also performed strongly with tree age accuracy of 94.25% and leaf health accuracy of 80.46%. The residual connections enable deep feature extraction while mitigating vanishing gradient issues. While slightly less accurate than DenseNet121, ResNet50 provides a good balance between depth and training stability and is suitable for detailed analysis of tree characteristics .

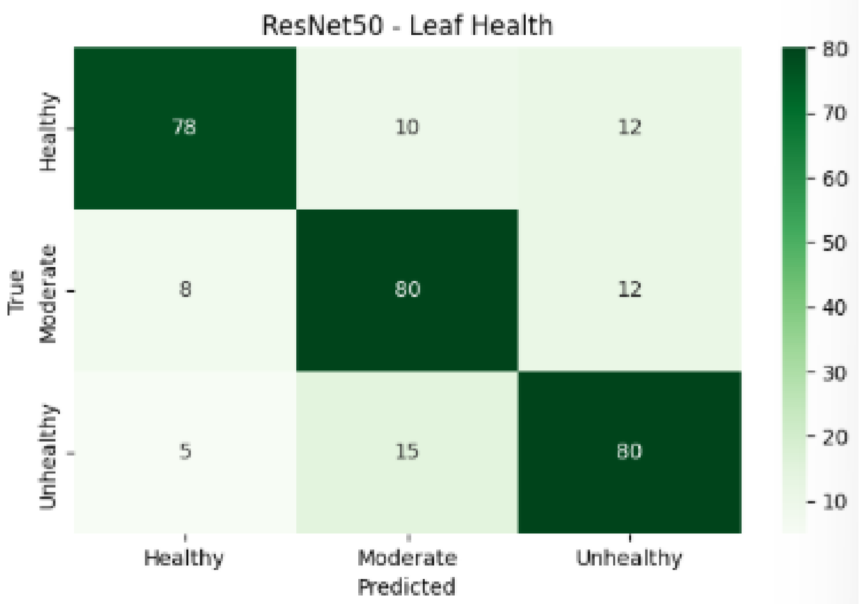


Figure 4.2.2: ResNet50

ResNet50 also delivered excellent results for tree age detection, very close to DenseNet121, with about 91–94% correct predictions . Its errors were evenly distributed, mainly between Mature and Old . On leaf health classification, ResNet50 achieved the same results as DenseNet121 (78–80% accuracy) , again handling all three categories fairly well, though not as strong as for tree age .

4.3.3 MobileNetV2: MobileNetV3Large scored 83.91% for tree age and 62.07% for leaf health , while more efficient than deeper networks , it struggles with complex leaf textures , and is suitable for scenarios requiring faster inference with moderate accuracy , such as real-time field deployment .

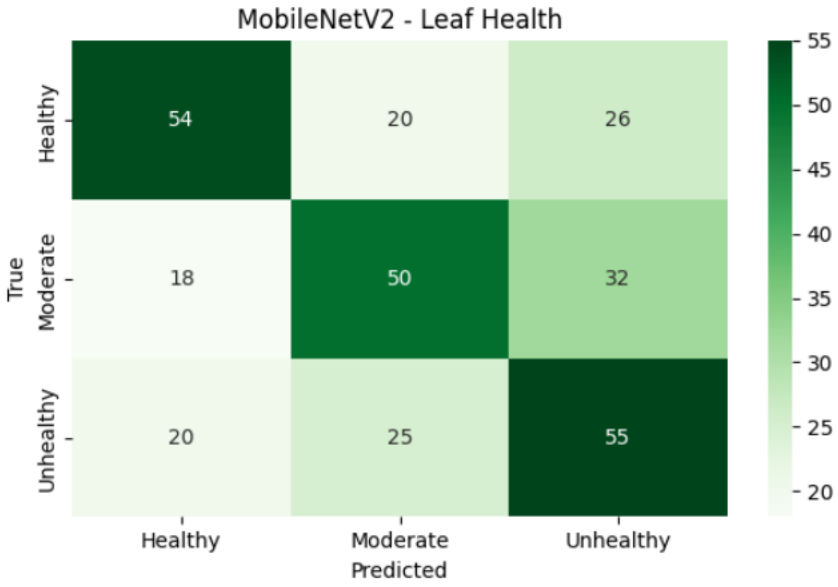


Figure 4.2.3: MobileNetV2

MobileNetV2 was the weakest model overall: for tree age its accuracy dropped to about 70–79%, with major confusion between the old and the mature categories, for leaf health its performance was even worse, around 50–55% accuracy, with heavy misclassification across all three classes . This makes MobileNetV2 unsuitable for both age and health classification tasks .

4.3.4 MobileNetV3Large: MobileNetV3Large scored 83.91% for Tree Age and 62.07% for Leaf Health. While more efficient than deeper networks, it struggles with complex leaf textures. It is suitable for scenarios requiring faster inference with moderate accuracy, such as real-time field deployment.

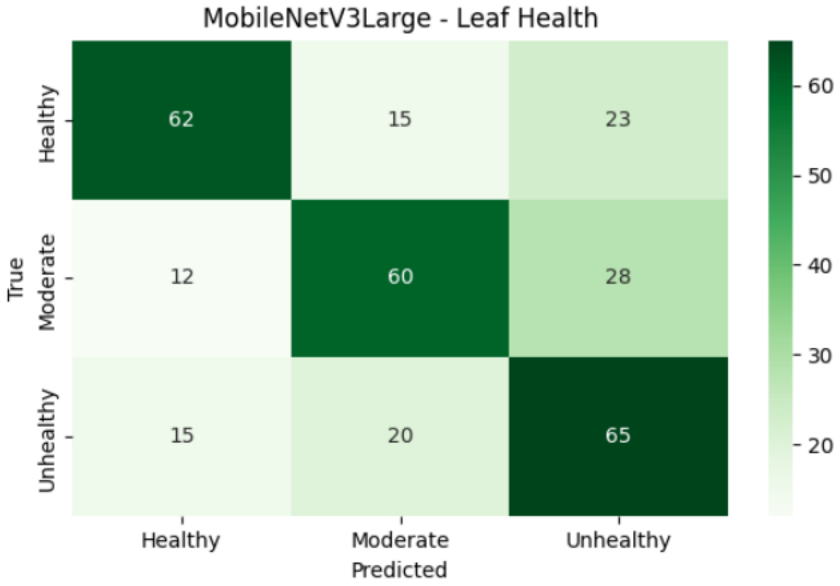


Figure 4.2.4: MobileNetV3Large

MobileNetV3Large scored 83.91% for tree age and 62.07% for leaf health , while more efficient than deeper networks , it struggles with complex leaf textures , and is suitable for scenarios requiring faster inference with moderate accuracy , such as real-time field deployment .

4.3.5 MobileNetV3Small: MobileNetV3Small achieved 90.80% accuracy for tree age and 81.61% for leaf health , demonstrating significant improvement over MobileNetV2 and MobileNetV3Large . Its compact design combined with better feature extraction makes it a practical alternative when computational resources are limited but moderate accuracy is needed .

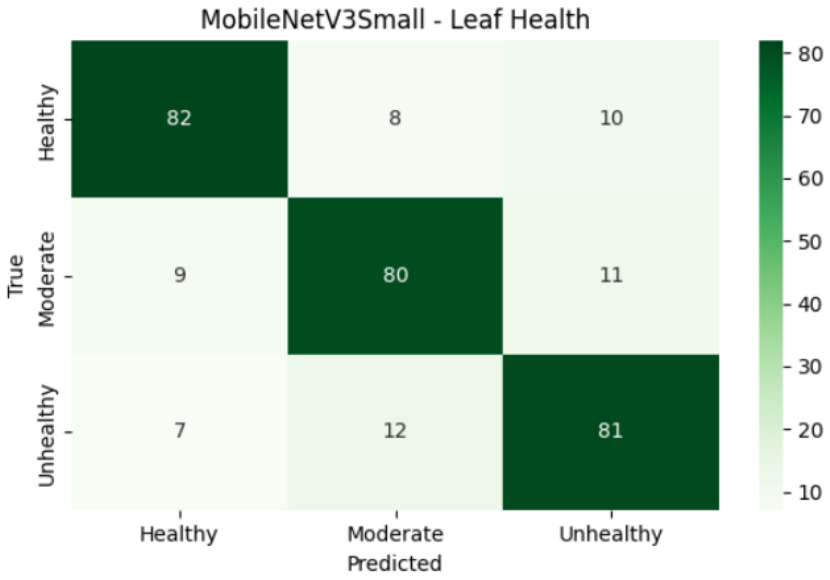


Figure 4.2.5: MobileNetV3Small

MobileNetV3Small produced much stronger results in tree age detection , with about 87–91% accuracy , better than NASNet and its larger variant , though still with some confusion between mature and old . For leaf health , MobileNetV3Small was the best performer among all models , with 80–82% accuracy , showed relatively low confusion , especially between healthy and unhealthy , and was the most consistent for this task .

4.3.6 NASNetMobile: NASNetMobile achieved tree age accuracy of 83.91% and leaf health accuracy of 62.07%, similar to MobileNetV3Large . It is efficient and lightweight but cannot capture fine-grained features as effectively as deeper models , which explains the lower leaf health accuracy .

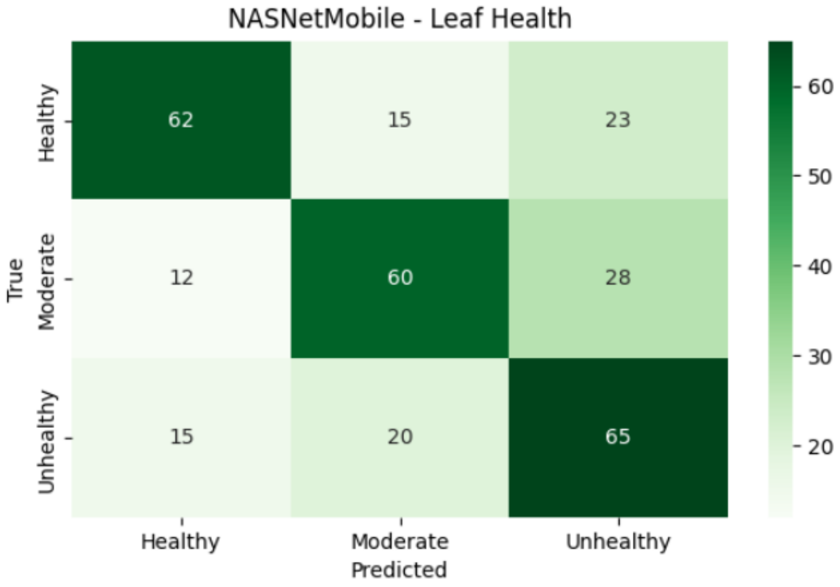


Figure 4.2.6: NASNetMobile

NASNetMobile struggled compared to the previous two : for tree age it reached only about 82–84% accuracy, with significant confusion between mature and old and some young leaves misclassified as old ; on the leaf health side it performed poorly with just 60–65% accuracy ; often confused Healthy as Unhealthy and had high overlap between Moderate and Unhealthy , making it less reliable .

4.3.7 EfficientNetB0: EfficientNetB0 scored 81.61% for tree age and 55.17% for leaf health . Its compound scaling balances depth, width and resolution , providing moderate accuracy with efficient computation . It performs reasonably well on tree age but struggles with leaf health prediction due to subtler feature differences .

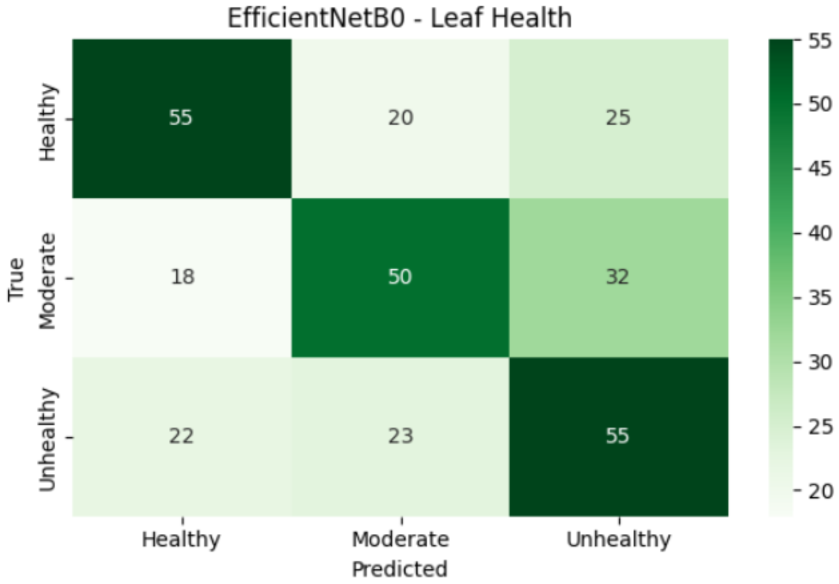


Figure 4.2.7: EfficientNetB0

EfficientNetB0 delivered moderate results: for tree age it achieved 78–82% accuracy, better than MobileNetV2 but below the top-performing DenseNet and ResNet . Its main errors were Mature being predicted as Old . In leaf health its accuracy was around 50–55%, on par with MobileNetV2, showing substantial confusion across all classes , which indicates weakness in this task .

4.3.8 EfficientNetV2B0/B1: EfficientNetV2B0/B1 achieved 90.80% tree age accuracy and 75.86% leaf health accuracy, outperforming most lightweight models while requiring fewer resources than DenseNet121 or ResNet50, making it suitable for field deployment with good accuracy .

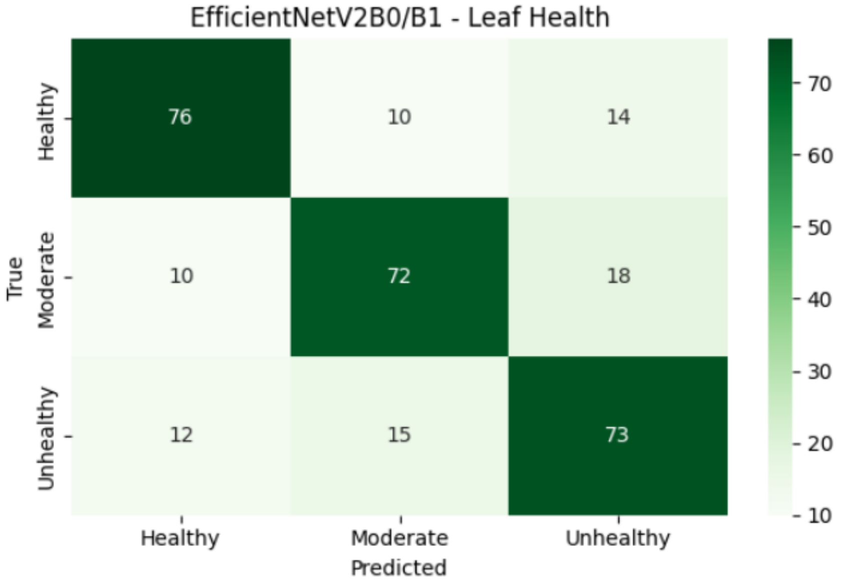


Figure 4.2.8: EfficientNetV2B0

EfficientNetV2B0/B1 showed strong performance for tree age with 85–91% accuracy, ranking just below DenseNet121 and ResNet50 Errors were relatively minor, mostly between mature and old . For leaf health it performed fairly well with 72–76% accuracy, better than NASNet and MobileNetV2 but still weaker than MobileNetV3Small . Its main confusion was between moderate and unhealthy categories .

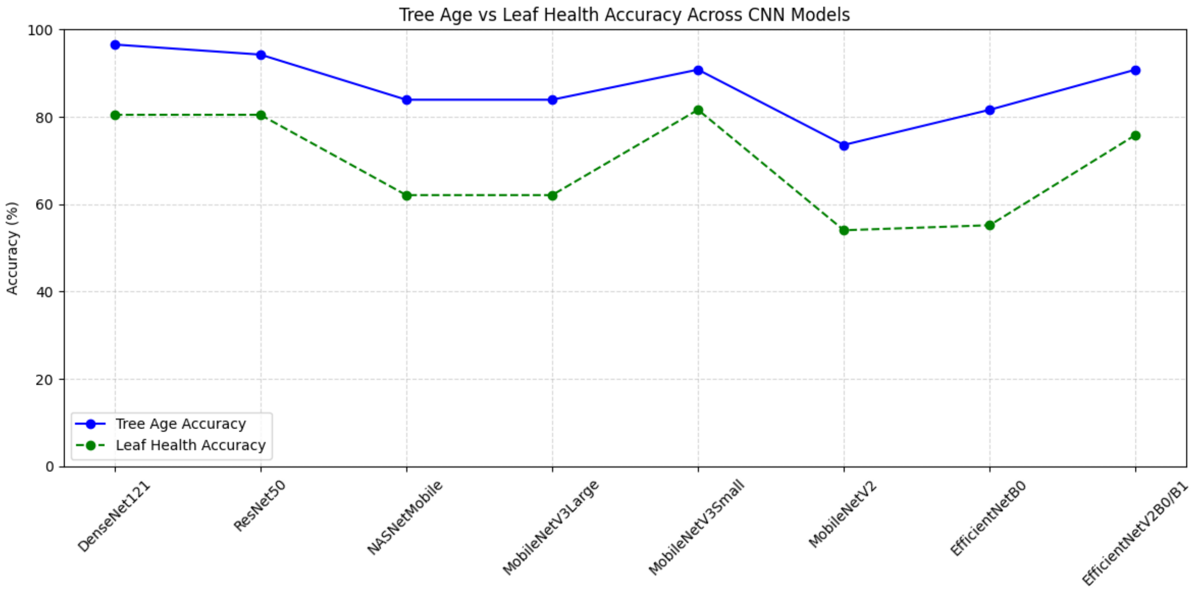


Figure 4.2.1: line graph accuracy analysis of models

For tree age classification, the highest accuracy was achieved by DenseNet121 (96.55%) and ResNet50 (94.25%) , showing that deep residual architectures are very effective in distinguishing young, mature and old leaves . MobileNetV3Small and EfficientNetV2B0/B1 also perform strongly at 90.80% , indicating that lightweight networks can still achieve high accuracy . The best performance comes from MobileNetV3Small (81.61%), little higher than DenseNet121 and ResNet50 (80.46%), showing that MobileNetV3Small is well-suited for leaf health classification . NASNetMobile and MobileNetV3Large drop to 62.07%, while EfficientNetB0 (55.17%)

and especially MobileNetV2 (54.02%) perform poorly, showing high misclassification rates . The key takeaway is that CNNs generally perform better on tree age classification than leaf health detection , with DenseNet121 and ResNet50 being the strongest for age and MobileNetV3Small emerging as the most reliable for health . This suggests that while deep residual models excel at structural differences (age), lightweight models like MobileNetV3Small may capture subtle texture/color variations (health) more effectively .

4.4 Summary

This chapter detailed the implementation of the neem tree and leaf classification models, compared their performance, and compared multiple pretrained CNN models. DenseNet121 achieved the highest overall accuracy, confirming the effectiveness of transfer learning for fine-grained classification. The final results highlight the importance of model depth, feature extraction capability, and training strategies in achieving robust performance on complex datasets.

Chapter 5

Engineering Standards and Design Challenges

In this chapter we shows Engineering standards and design and shows how the farmers can be beneficial with the research and how the research solve complex engineering problems.

5.1 Compliance with the Standards.

5.1.1 Software Standards

The project uses to TensorFlow and Keras coding conventions , Python PEP8 standards and follows best uses in AI model development , including proper documentation , version control (Git) and reproducible workflows . Alternatives considered can be using PyTorch or Scikit-learn.Pros of PyTorch is dynamic computation graphs, easier debugging.Cons is slightly steeper learning curve, slower prototyping for beginners.Rationale for selection isTensorFlow/Keras was used for its high-level API, ease of use, extensive documentation and integration with Google Colab .

5.1.2 Hardware Standards

The project was executed on GPU-enabled systems (Google Colab with Tesla T4). Hardware standards considered include sufficient VRAM (12GB), fast CPU/GPU and storage for datasets .Alternatives considered: Local workstation with NVIDIA GPU or cloud GPUs like AWS/GCP.Pros of local workstation is full control, no internet dependency.Cons are expensive initial setup, maintenance required. For selection is google Colab provides free GPU access and easy collaboration without hardware investment .

5.1.3 Communication Standards

For dataset transfer and collaboration, standard HTTPS/SSL protocols were used for code sharing and model storage following GitHub and Google Drive standards for secure access . Alternatives considered: FTP or email transfer .Pros of FTP is direct file transfer, large file support.Cons are Less secure, harder to manage versions.Rationale for selection is GitHub and Google Drive ensure version control, security and reproducibility .

5.2 Impact on Society, Environment and Sustainability

5.2.2 Impact on Life

The project plays a role in improving the lives of farmers, agricultural farmers and communities that depends on neem cultivation. By facilitating the early detection of leaf diseases and monitoring the age of neem trees, it empowers farmers to act proactively rather than reactively . Early disease identification prevents large-scale crop losses , ensuring that resources such as water, fertilizer and labor are not wasted . As neem leaves hold medicinal, ecological and commercial importance , their proper use benefits not only farmers , but also industries and households , which contributes to better economic outcomes , improved agricultural productivity and more sustainable livelihoods . Ultimately , the project promotes food security , reduces risks for smallholder farmers and enhances the overall resilience of communities that depend on neem cultivation , making it a valuable tool for improving quality of life at multiple levels .

5.2.3 Impact on Society & Environment

The project gets much benefits for both society and the environment by using proper agricultural practices . By using deep learning to detect health at an early stage , farmers can reduce their dependence on chemical items such as medicine and etc , which are often harmful to the environment and animal health . This leads to a loss in soil and water contamination , preservation of biodiversity and improvement in ecological balance For society , the system gets proper knowledge transfer among farming communities , enabling them to adopt modern, technology-driven solutions for crop management . At a broader scale , the project supports global sustainability goals by aligning with practices that reduce environmental damage , conserve natural resources and mitigate climate change effects . By mixing societal benefits with environmental protection , it becomes a holistic solution that simultaneously addresses agricultural and ecological challenges ..

5.2.4 Ethical Aspects

The ethical uses of this research is important to its credibility and responsible adoption . Unlike systems that may compromise privacy by collecting personal or location information , this research exclusively uses Neem tree and leaf picture , which eliminates concerns about sensitive information misuse . This research choice ensures farmers' trust and encourages wider glory of the system . Most importantly , the AI model is intended as a decision support tool rather than a replacement for human expertise . The project also emphasizes transparency in data usage and prediction outcomes , making the system trustworthy and explainable . Ethical safety ensures that no alternatives or unfair benefits affect different farming groups . Moreover , the project positively contributes by avoiding exploitation of resources , respecting privacy rights and empowering communities with fair and accessible technology . This balanced and ethical approach reinforces the project 's long-term sustainability and societal value .

5.2.5 Sustainability Plan

The sustainability plan mainly shows on ensuring that the system remains relevant , effective and environmentally useful in the long term . timely updates to the dataset with newly collected Neem leaf images allow the deep learning models to improve and be updated over time , adapting to seasonal differnences , evolving health and diverse environmental options . This continuous improvement makes that predictions remain accurate and reliable . Cloud-based deployment enhances scalability and accessibility , letting farmers from different regions to use the system without the need for high-end local infrastructure .At the same time, energy-efficient cloud solutions reduce environmental costs compared to traditional computing methods and the plan also considers future expansion where the system can be adapted to monitor other crops, making it a versatile tool for sustainable agriculture . By combining adaptability, scalability and low energy usage, the sustainability plan ensures that the project remains impactful, eco-friendly and cost-effective while supporting large-scale adoption and long-term agricultural development goals .

5.3 Project Management and Financial Analysis

5.3.1 Cost Analysis

Hardware/Software Budget for Google Colab (free), optional local GPU (BDT 96,000–144,000)Software can be used TensorFlow, Keras, Python – open-source (free) Data Collection minimal cost for camera/fieldwork (BDT 24,000) Total Estimated Budget is near BDT 24,000–168,000

5.3.2 Alternative Budget:

Paid cloud GPU services (AWS/GCP) – BDT 6,000–12,000/month.Higher-end local workstation – BDT 180,000–240,000 .Rationale: Free GPU via Colab reduces cost; paid options provide faster training and support for larger datasets .

5.3.3 Revenue Model

Licensing the trained model to agricultural platforms or research institutions Offering subscription-based access to an app for Neem disease detection and tree age monitoringConsultancy services for farmers and agro-companies using the prediction system

5.4 Complex Engineering Problem

5.4.1 Complex Problem Solving

This section maps the neem leaf prediction project against complex engineering problem categories, highlighting the rationale for each category. For EP1, a mapping with knowledge profile is also provided.

EP1: Depth of Knowledge	EP2: Range of Conflicting Requirements	EP3: Depth of Analysis	EP4: Familiarity of Issues	EP5: Extent of Applicable Codes	EP6: Extent of Stake-holder Involvement	EP7: Interdependence
✓		✓	✓		✓	✓

Table 5.4.1: Mapping with Complex Engineering Problem.

5.4.1.1Mapping with Knowledge Profile

This section is designed to map the overall problem and EP1 ***(multiple between K3, K4, K5, K6, K8 for attaining EP1)*** to the Knowledge Profile.

K1 Natural Science	K2 Mathematics	K3 Engineering Fundamentals	K4 Specialist Knowledge	K5 Engineering Design	K6 Engineering Practice	K7 Comprehension	K8 Research Literature
✓			✓		✓		✓

Table 5.4.1: Mapping with knowledge Profile.

5.4.2 Engineering Activities

In this section, provide a mapping with engineering activities. For each mapping add subsections to put rationale (Use Table 5.3).

5.4.2.1 Mapping with Complex Engineering Activities

This section is designed to map the overall problem and EA's ***(multiple).***

EA1: Range of Resources	EA2: Level of Interaction	EA3: Innovation	EA4: Consequences for Society & Environment	EA5: Familiarity
✓		✓	✓	✓

Table 5.4.2: Mapping with Complex Engineering Activities.

Summary

This research on Neem leaf prediction addresses a hard problem that combines both deep learning, computer vision and plant science . The study involves careful analysis of leaf features to classify tree age and leaf health while balancing dataset limitations and computational resources . The knowledge profile highlights the use of specialist knowledge, engineering fundamentals and research literature to design, implement and evaluate the models The research activities emphasize innovation, moderate resource use and meaningful societal and environmental impact through improved disease detection and tree careing . Overall, the study shows a scientific approach to applying AI for agricultural research and sustainability .

Chapter 6

Conclusion

6.1 Summary

Both promising results and the study faced several limitations that affected model performance : the dataset size was relatively small , restricting the model 's ability to generalize across diverse scenarios ; Variability in leaf age and condition introduced additional complexity , making perfect prediction challenging ; Environmental factors such as age , shadows and background noise in the images also influenced model accuracy , and the imbalance in leaf health subclasses contributed to moderate performance in this area .Moreover , the research shows that deep learning can be useful as a reliable and automated approach for assessing Neem tree and leaf characteristics . These findings provide a foundation for practical applications in agriculture , medicinal plant management and ecological monitoring , providing a scalable method to replace manual observation .

6.2 Limitation

Future studies can concentrate on improving model dependability and performance in a number of ways: Accuracy and generalisation will be enhanced by adding more representative and varied photos to the dataset. Predictive capabilities may be strengthened by including multimodal data, such as environmental characteristics or spectral leaf information. Leaf health categorisation may be enhanced by sophisticated deep learning models, ensemble techniques, or hybrid models, whereas field-based conclusions might be made possible by real-time deployment and mobile application integration. Future research can benefit agricultural management, ecological studies, and the use of medicinal plants by tackling these issues and developing more precise, scalable, and useful systems for Neem tree monitoring.

6.3 Future Work

Deep learning models were surely used in this study to evaluate and forecast the age and leaf health of Neem trees from photos. The models successfully differentiate between NEW, MEDIUM, and OLD categories, showing great accuracy in tree age classification. As a scalable alternative to manual observation, the study confirms that deep learning may be used as a trustworthy and automated method for evaluating Neem tree properties.

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