CHAPTER 1
INTRODUCTION

1.1 Background

Lemongrass (Cymbopogon citratus) is a tropical herbal plant with high economic value and health benefits. This plant is widely used in the food, pharmaceutical and cosmetic industries due to its high content of citral compounds in its essential oil [2], [3]. In countries such as Indonesia and India, lemongrass is also traditionally used as a natural remedy and insect repellent [4], [5]. Furthermore, lemongrass has potential as an antibacterial, antioxidant and antifungal agent, leading to its expanding applications [2], [6]. However, lemongrass cultivation faces various agronomic challenges, such as stress from climate change, nutrient deficiencies, and pathogen attacks. Physiological and morphological changes in lemongrass leaves caused by biotic and abiotic stress often serve as primary indicators of declining plant quality and productivity [3], [4], [7]. Early detection of leaf conditions is crucial to mitigate losses. Unfortunately, most of the leaf condition identification methods used by farmers are manual and subjective, prone to errors, and require specialized expertise. The health of lemongrass plants plays a crucial role in determining the productivity and quality of the essential oil they produce. Research indicates that lemongrass plants that are well-nourished and free from pests/diseases produce higher quantities of superior-quality essential oil. Factors such as optimal soil conditions, proper fertilization, and adequate water supply contribute to better plant growth, resulting in increased biomass and higher essential oil content [8]. In contrast, plants stressed by poor soil quality, insufficient nutrients, or inadequate water availability produce lower results and also produce lower quality essential oil [9]. Therefore, maintaining the general health of lemongrass plants is crucial to maximize productivity and essential oil quality, highlighting the importance of providing suitable growing conditions to ensure the well being of the plant [10]. Early detection of leaf conditions is essential to mitigate losses. Unfortunately, most of the leaf condition identification methods used by farmers are manual and subjective, prone to errors, and require specialized expertise.

In this context, artificial intelligence-based computer vision technology offers a solution to automatee process of classifying plant leaf conditions quickly and accurately. In particular, the Convolutional Neural Network (CNN) method has been shown to be effective in recognizing complex visual patterns in various types of plants, including apple, tomato and grape leaves [11]. In a study conducted by Patil et al. and published in Data in Brief, a comprehensive lemongrass leaf data set was provided [1]. Although various machine learning models have been tested on this dataset, the main challenge faced is achieving high accuracy in disease detection for the InceptionV3 (89.50%) and Xception (94.67%) models, which are less than satisfactory. Previous studies have demonstrated that the application of image augmentation techniques can improve the performance of CNN models, especially when the amount of training data is limited. Dewantara et al. applied a stepwise augmentation approach involving geometric transformations and distortions for the classification of rare orchids, and the results showed a significant improvement in the precision of the model [12]. Mahesh found that the combination of techniques such as flipping, rotation, and color jitter effectively improved the accuracy of medical image classification to 99% [13]. Lijo compared ResNet50, DenseNet169, and InceptionV3 in detecting plant diseases and found that applying augmentation increased the precision of ResNet50 from 97.3% to 98.2% [14]. On the other hand, the transfer learning approach using pre-trained models such as ResNet, MobileNet, and Inception has been widely used in plant image classification and leaf disease detection tasks, thanks to its high efficiency and accuracy. Prajwala et al. [15] used a lightweight CNN architecture to detect tomato leaf diseases and achieved a classification accuracy of 94–95% on a specific tomato leaf dataset. In 2020, Shelar et al. [16] developed a basic CNN model for general plant disease recognition. In another study, Chugh et al. [17] applied the InceptionV3 architecture to detect potato leaf diseases, such as early blight and late blight, although the specific accuracy was not explicitly stated. A more comprehensive study was conducted by Saleem et al. [18] through the evaluation of various CNN architectures and optimization algorithms. The results showed that the Xception architecture trained using the Adam optimizer achieved a validation accuracy of 99.81% with an F1-score of 99.78%. Sagar and Jacob [19] conducted a comparative study of several CNN architectures, such as VGG16, ResNet50, InceptionV3, InceptionResNet, and DenseNet169, using the PlantVillage dataset. The best results were obtained from ResNet50 with an accuracy of 98.2% and an F1-score of 94%. Furthermore, Hassan et al. [20] emphasized the importance of the transfer learning approach in leaf image classification, as demonstrated by the high performance of EfficientNetB0 with an accuracy of 99.56%. The trend in 2023 shows a tendency to combine CNN with augmentation and segmentation techniques to improve model performance. Gogoi et al. [21] developed a three-stage CCNN model combined with transfer learning to detect rice leaf diseases, achieving an accuracy of 94% despite using a limited dataset. Hajam et al. [22] proposed a transfer learning and fine-tuning-based ensemble model combining VGG19 and DenseNet201, achieving an accuracy of 99.12% in classifying 30 types of medicinal plant leaves. Serttas and Deniz [23] applied a transfer learning approach to the VGG16, ResNet50, and MobileNetV2 architectures for detecting bean leaf diseases, with the best results obtained from ResNet50, which achieved an accuracy of 98.33%. Gulzar [24] also successfully implemented TL-MobileNetV2 based on transfer learning for the classification of 40 types of fruits, with an accuracy and F1-score of 99%. Islam et al. [25] developed an efficient hybrid model based on VGG16 and ResNet50 for plant disease detection, with an accuracy of 95.89%. Faurina et al. [26] compared the performance of several CNN architectures in classifying food crop diseases using a transfer learning approach on the agroAI dataset. The best results were obtained from ResNet50, which achieved 100% testing accuracy in chili classification. Abdul Azis et al. [27] used EfficientNetB0 to classify 10,407 rice leaf images and achieved an accuracy of 98.86% and an F1-score of 99.70%. Meanwhile, Saluja et al. [28] applied an ensemble CNN approach combined with GoogleNet for plant disease classification across 10 different plant species, achieving a final accuracy of 99.07%.

Prior research has demonstrated that combining image augmentation techniques with transfer learning can substantially improve the classification accuracy of Convolutional Neural Networks (CNNs) for plant disease detection. However, in the specific context of lemongrass (*Cymbopogon citratus*) leaf condition classification, the systematic evaluation of these techniques remains limited—particularly regarding the comparative performance of diverse CNN architectures when applied to the same dataset and task. This study aims to fill that gap by thoroughly assessing the effectiveness of transfer learning and fine-tuning across five carefully selected pre-trained CNN models: InceptionV3, Xception, MobileNetV2, ResNet152V2, and DenseNet201. These models were not chosen arbitrarily; each represents a distinct architectural design philosophy. For instance, MobileNetV2 is optimized for lightweight deployment with efficient depthwise separable convolutions, making it ideal for real-time mobile applications. ResNet152V2 leverages very deep residual learning to capture complex hierarchical patterns, while DenseNet201 enhances feature reuse through dense connections. InceptionV3 and Xception offer hybrid multi-scale feature extraction and spatial efficiency through inception modules and separable convolutions, respectively. The goal of this research is not only to determine which CNN model yields the highest accuracy but also to understand which architectural characteristics are most suitable for distinguishing between the three classes of lemongrass leaf conditions—Dried, Healthy, and Unhealthy—under practical constraints. By integrating structured augmentation and fine-tuning strategies into the evaluation pipeline, this study seeks to inform the design of accurate and computationally efficient computer vision systems for precision agriculture, particularly in sustainable lemongrass cultivation.

1.2 State of the Art

The classification of plant leaf conditions using Convolutional Neural Networks (CNNs) has become a cornerstone in modern agricultural image analysis, particularly for disease detection and plant health monitoring. Numerous studies have successfully applied transfer learning on CNN architectures such as InceptionV3, ResNet152V2, DenseNet201, MobileNetV2, and Xception to identify diseases in various crops, including apple, tomato, and rice [29–33].

To further enhance model performance, especially under limited training data, image augmentation techniques such as rotation and flipping have been widely adopted. These techniques simulate real-world variability and improve model generalization.

Despite the availability of a high-quality lemongrass leaf dataset introduced by Patil et al. [1], research efforts specifically targeting the classification of lemongrass (*Cymbopogon citratus*) leaf conditions remain limited. Most existing studies either examine only a small subset of CNN models or do not include thorough fine-tuning and augmentation protocols. Moreover, no prior work has systematically compared a diverse set of CNN architectures using a unified experimental framework for lemongrass classification.

To address this gap, the present study aims to comprehensively assess the effectiveness of applying transfer learning and fine-tuning techniques on five pre-trained CNN models—InceptionV3, Xception, MobileNetV2, ResNet152V2, and DenseNet201—for classifying lemongrass leaf images into three categories: Dried, Healthy, and Unhealthy. These models were selected not only for their proven success in plant classification tasks but also due to their distinct architectural characteristics that reflect a spectrum of design strategies. For example, MobileNetV2 is designed for lightweight and efficient inference, suitable for mobile-based agricultural tools [32], whereas ResNet152V2 uses deep residual learning to effectively model complex features in deep architectures [30]. DenseNet201 strengthens feature reuse through dense connectivity [31], while InceptionV3 and Xception emphasize multi-scale feature extraction and computational efficiency, respectively [29, 33].

By evaluating these five models under consistent conditions—including structured image augmentation and fine-tuning strategies—this study aims not only to identify the most suitable CNN model for lemongrass leaf classification but also to understand how specific architectural features influence classification performance. The findings are expected to contribute to the design of accurate and efficient computer vision systems for precision agriculture and sustainable lemongrass cultivation.

1.3 Research Problem

Based on the gaps identified in the state of the art review, the main research problem addressed in this study is as follows:

1. How does the application of transfer learning combined with fine-tuning influence the performance of five pre-trained CNN architectures—InceptionV3, Xception, MobileNetV2, ResNet152V2, and DenseNet201—in classifying lemongrass (*Cymbopogon citratus*) leaf conditions into three categories: Dried, Healthy, and Unhealthy?

1.4 Research Objective

The objectives of this study are:

1. Investigate the impact of transfer learning and fine-tuning on the performance of five pre-trained CNN models—InceptionV3, Xception, MobileNetV2, ResNet152V2, and DenseNet201—in classifying lemongrass leaf conditions.
2. Implement a standardized image augmentation strategy across all models to improve model generalization under limited data conditions.
3. Identify the most effective CNN architecture for lemongrass leaf classification based on a comprehensive evaluation of accuracy, precision, recall, F1-score, and AUC metrics.

1.5 Research Methodology

This study adopts a quantitative experimental approach using digital image data of lemongrass leaves. The research process is structured into several key stages, as illustrated in the proposed scheme:

1. **Data Acquisition:** The process begins with the utilization of a publicly available lemongrass (*Cymbopogon citratus*) leaf dataset, which is pre-categorized into three classes: Dried, Healthy, and Unhealthy.

2. **Dataset Splitting:** The dataset is divided into training, validation, and test sets using stratified sampling to ensure balanced class distribution across subsets.

3. **Data Pre-processing and Image Augmentation:** Input images undergo standardized preprocessing using `preprocess_input` from Keras. Augmentation is applied via `ImageDataGenerator`, including transformations such as rotation, flipping, zooming, and brightness variation to improve generalization.

4. **Transfer Learning Initialization:** Each CNN model is loaded with pre-trained ImageNet weights. All convolutional base layers are frozen to preserve learned features.

5. **Initial Training:** A new dense classifier is added to the top of each model. Only the classifier head is trained during this stage while the base remains frozen.

6. **Fine-Tuning:** Selective layers of the CNN base are unfrozen and retrained with a reduced learning rate to adapt feature extraction to the lemongrass dataset.

7. **Evaluation and Analysis:** Performance is measured using accuracy, precision, recall, F1-score, confusion matrix, and ROC-AUC. Comparative analysis is supported by visualizations such as learning curves and confusion matrices.

1.6 Scope of Work

The scope of this study is limited to the following aspects:

1. **Data Type:** This research exclusively utilizes digital images of lemongrass (*Cymbopogon citratus*) leaves.

2. **Classification Scope:** The classification task focuses on three categories: Dried, Healthy, and Unhealthy.

3. **CNN Architectures:** Evaluation is restricted to five pre-trained CNN models: InceptionV3, Xception, MobileNetV2, ResNet152V2, and DenseNet201.

4. **Development Environment:** All experimentation is conducted using Python, leveraging TensorFlow and Keras deep learning frameworks.

1.7 Timeline

The details of research timeline will show as table 1.1 below:

Table 1.1 Research Milestone

No	Activity	2024							
		May	June	July	August	Sept	Oct	Nov	Des
1	Research Proposal Preparation								
2	Proposal Seminar Presentation								
3	Program Development								
4	Result Analysis								
5	Thesis Progress Monitoring								
6	Journal Article Submission								
7	Thesis Defence								