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Detection of Tea Leaf Diseases Using Deep Transfer Learning

By

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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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APPROVAL

This Project titled **"Detection of Tea Leaf Diseases Using Deep Transfer Learning"**, submitted by Name **Anzim Tasrif Athoi**, ID No: **211-15-14660** 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 **Israt Jahan, Lecturer (Senior Scale)**, 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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ABSTRACT

One of the most serious plant diseases to the production of tea is the tea leaf disease. In the early stages, it often shows no visible symptoms, making early detection difficult until the infection spreads across the leaf. As a result, tea leaf disease is considered a leading cause of crop loss in tea plantations. This paper suggests that deep learning models, specifically the transfer learning and the ensemble approach, could be deployed in the automation of tea leaf disease detection. First of all, the dataset was pre-treated, and several data augmentation methods were implemented, such as resizing, rescaling, flipping, rotation, zooming, and contrast adjustment.We then conducted Error Level Analysis (ELA) to identify any patterns that may have been overlooked in the images. The research explored deep learning models capable of accurately distinguishing between different classes of the disease. Pre-trained models such as EfficientNetB0 and EfficientNetV2B1 were employed for transfer learning. Furthermore, ensemble models combining CNN with EfficientNetB0 and CNN with EfficientNetV2B1 were evaluated. All models were tested using two approaches: ordinal classification and regular classification. Among the transfer learning models, EfficientNetB0 achieved the highest accuracy of 91.91% with ordinal classification. Within the ensemble models, CNN+ EfficientNetB0 reached a peak accuracy of 89.04% under ordinal classification. These models can assist agronomists and tea farmers, particularly those with limited resources, by enabling effective identification and classification of tea leaf disease.

Keywords: Tea leaf disease, Deep Learning, Transfer Learning, Ensemble model and Convolutional Neural Network.

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Chapter 1

Introduction

1.1 Introduction

Tea is a vital commercial crop in conventional farming systems. The global demand for tea remains substantial. Annual global tea output surpasses USD 1.7 billion, while the international tea market is estimated at around USD 9.5 billion [1]. Ensuring the healthy development of tea plants and preserving tea quality is crucial to advancing the tea sector. Pests and diseases pose serious threats to tea cultivation, often resulting in decreased yields and compromised quality, thereby inflicting considerable financial setbacks on tea growers and producers [2]. Conventional detection approaches include expert-based identification, molecular techniques, and spectroscopic analysis. Manual evaluation by specialists faces limitations such as being time-intensive, highly subjective, and relatively inaccurate. Moreover, employing specialists for on-site inspections is both expensive and labor-demanding [3]. Although molecular diagnostics and spectroscopy yield more precise outcomes, they demand substantial training and costly equipment [4]. Consequently, exploring reliable and efficient methods for detecting tea pests and diseases holds substantial importance.

It has identified transfer learning as an important strategy for tea leaf disease detection, especially to address the challenges of limited image data sets [5]. It uses deep learning models trained on a large dataset,such as ImageNet. Applying models for deep learning on transfer learning, ImageNets has enabled us to adapt this data set for disease detection and extra significant features from a limited amount of data [6]. Ensemble learning has been identified as a powerful method for combining multiple models to identify diseases and improve performance [7]. This can introduce a feature that exploits model diversity that can further improve ensemble learning methods and reduce the risk of overfitting.This makes it possible to make accurate and reliable predictions [8]. It is possible to accurately assess each disease class using an integrated approach for tea leaf disease identification, where subtle changes in the image require analyzing it from different perspectives. This method has shown promise in improving the accuracy of diagnosis, leading to effective treatment of the disease [9].

Although a transfer learning and ensemble learning sample lane have proven promising in disease detection,they have some limitations. In the case of transfer learning, using image nets, it has domain gaps in the image data, which can hinder the learning features [10]. It is also possible to adjust lighting from pre-trained models within transfer learning [11]. With the continual advancement of computer vision technologies, research into automated detection and classification of tea plant afflictions is gaining momentum. Image processing and machine learning strategies are increasingly being deployed for pest and disease identification in tea crops. These approaches typically involve segmenting diseased regions and extracting visual traits, leading to significant progress.In traditional machine learning applications for plant disease recognition, hand-crafted feature extraction remains essential. Due to the prevalence of diseased leaves and their visual resemblance in terms of color, texture, and patterns, manual extraction plays a pivotal role in determining model performance. However, this process tends to be laborious and inherently biased [12].

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The objective of this paper is to utilize deep learning techniques to effectively categorize various stages of tea leaf based on tea leaf disease images. We have established two types of methods to easily classify each class of tea leaf disease.

- First, we used transfer learning techniques where EfficientNetB0, EfficientNetV2B1, and Resnet50 were used for ordinal and regular classification which can accurately detect lung cancer.

- Finally, we used two ensemble models, the first one is EfficientNetB0 + Basic CNN model, and the second one is EfficientNetV2B1 + Basic CNN model for ordinal and regular classification, which can accurately identify and classify

1.2 Motivation

Tea is among the most widely consumed beverages globally and serves as a crucial cash crop in numerous countries, such as Bangladesh, India, Sri Lanka, and China. The health of tea plants significantly influences both the quality and quantity of tea production. Nevertheless, diseases affecting tea leaves present a considerable challenge to sustainable cultivation, frequently resulting in substantial yield losses and economic difficulties for farmers. A primary issue is that these diseases often go undetected in their initial stages due to the lack of visible symptoms, which leads to delayed interventions and further damage to the crops. Conventional methods for disease detection necessitate manual inspections by specialists, which are not only time-intensive and expensive but also impractical for extensive plantations. In this regard, the incorporation of artificial intelligence and deep learning presents a promising avenue. Automated systems for disease detection can lessen the dependence on human expertise, reduce error rates, and furnish farmers with accessible, cost-effective tools for early diagnosis. By utilizing transfer learning and ensemble models, this research aims to enhance the accuracy and dependability of tea leaf disease detection. The driving force behind this study is to equip tea farmers, especially those with limited technical and financial means, with a technology-driven strategy that guarantees improved crop protection, boosts productivity, and contributes to the overall advancement of the tea industry.

1.3 Objectives

The main objective of this study is to develop an automated and reliable deep learning–based system for detecting and classifying tea leaf diseases. To achieve this, the research sets out the following specific objectives:

1. To preprocess and augment the dataset utilizing methods such as resizing, rescaling, flipping, rotation, zooming, and contrast adjustment to enhance model generalization and robustness.
2. To implement Error Level Analysis (ELA) on the dataset to uncover hidden or subtle patterns in tea leaf images that may aid in improving classification.
3. To compare two classification strategies regular classification and ordinal classification to ascertain which approach yields superior accuracy and reliability

in disease detection.

4. To propose an efficient and cost-effective solution that can assist agronomists and tea farmers, particularly in resource-limited environments, by facilitating early and precise disease identification for enhanced crop management.

1.4 Methodology

The tea leaf detection classification system based on deep learning methodology will be identified in the systematic way of dataset, preprocessing, image augmentation, experimental setup, model selection, and training and evaluation of the model. The major steps involved include:

1. Dataset

   We used a total number of 23,676 images across six classes: Healthy, Heliopolis, Red Rust, Red Spider, Sunlight Scorching and Thrips. We took 3946 images in each class. Each image dimension is 800 x 800

2. Preprocessing

   To improve the performance of the model, we performed an Error Level Analysis (ELA). Using ELA. We were able to correctly identify each part of the image.

3. Image Augmentation

   Operations: resizing, rescaling, flipping, rotation, zooming, contrasting, convert to grayscale, normalization.

4. Experimental Setup

   The experiments were performed in a high-performance computing setup via Python, TensorFlow, and Kera's. The sample was separated into a training, validation and testing set of 80:10:10 each. Performance was evaluated by means of evaluation metrics like accuracy, precision, recall, and F1-score.

5. Model Selection

   Transfer Learning: The choices of EfficientNetB0 and EfficientNetV2B1 were transfer learning because they are efficient and highly perform tasks in image classification. CNN: CNN with EfficientNetB0 and CNN with EfficientNetV2B1

6. Model Training and Evaluation

   Optimized parameters for maximum performance. Early stopping and batch size tuning have been avoided to prevent overfitting. Measures: Accuracy, Precision, Recall, F1-score and Loss.

1.5 Project Outcome

The project effectively showcased the capabilities of deep learning methods for the automated identification of tea leaf diseases. The primary results are outlined below: Accurate Disease Detection: Among the various transfer learning models, EfficientNetB0 utilizing ordinal classification achieved the highest accuracy rate of 91.91%, whereas the CNN + EfficientNetB0 ensemble reached an accuracy of 89.04%. This indicates that both transfer learning and ensemble approaches are proficient in differentiating between healthy and diseased leaves. Improved Model Generalization: The implementation of data

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augmentation strategies, including rotation, flipping, zooming, and contrast modification, contributed to minimizing overfitting and enhancing the models' robustness. Enhanced Feature Representation: The application of Error Level Analysis (ELA) facilitated the identification of subtle differences in leaf textures that might not be apparent in unprocessed images, thereby aiding in superior feature extraction. Performance Evaluation: The research demonstrated that ordinal classification surpassed traditional classification methods, suggesting that taking into account the severity levels of diseases enhance the accuracy of predictions. Practical Implementation: The models created can be incorporated into a mobile or web-based diagnostic application, allowing tea farmers and agronomists to identify tea leaf diseases at an early stage, even in environments with limited resources. In summary, this initiative lays the groundwork for the implementation of AI-powered solutions in agriculture, minimizing crop losses and promoting sustainable tea production.

1.6 Organization of the Report

The report is structured into the following chapters to ensure a systematic presentation of the research:

Chapter 1: Introduction This chapter provides an overview of the background concerning tea leaf disease, its effects on tea production, the research problem, objectives, and the importance of utilizing deep learning techniques for disease detection.

Chapter 2: Literature Review This section presents a review of current studies related to plant disease detection through image processing, machine learning, and deep learning. It discusses the advantages and disadvantages of previous methods, laying the groundwork for the proposed methodology.

Chapter 3: Methodology This chapter details the research workflow, encompassing dataset collection, preprocessing, data augmentation, error level analysis (ELA), model selection, classification methods, and strategies for training and evaluation.

Chapter 4: Experimental Results and Analysis The findings from transfer learning and ensemble models are presented and examined. A comparative analysis of the performance between regular and ordinal classification is conducted using evaluation metrics including accuracy, precision, recall, F1-score, and confusion matrices.

Chapter 5: Project Outcome The results of the research are emphasized, detailing model performance, the benefits of ordinal classification, and the potential for implementation in real-world scenarios for tea farmers and agronomists.

Chapter 6: Conclusion and Future Work This chapter wraps up the study by summarizing the principal findings and contributions. It also proposes potential avenues for future research, such as enlarging the dataset, exploring other deep learning architectures, or implementing the system in a mobile application.

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Chapter 2

Background

2.1 Introduction

Tea is among the most widely consumed beverages globally and serves as a significant source of income for numerous countries, including Bangladesh. Nevertheless, the production of tea encounters considerable challenges due to leaf diseases, which adversely affect both yield and quality. The early identification of these diseases is often challenging, as visible symptoms typically manifest only after the infection has progressed. Conventional manual inspection methods are labor-intensive, subjective, and necessitate expert knowledge. With the progress in artificial intelligence, especially deep learning, the automated detection of plant diseases has become feasible. By utilizing image classification techniques, farmers and agronomists can more accurately and efficiently identify tea leaf diseases, thereby aiding in the prevention of crop losses and promoting sustainable tea production.

2.2 Literature Review

Artificial intelligence (AI) and deep learning applications in the agriculture sector have been actively developed over the last few years particularly in plant disease detection. The traditional methods of disease detection with the help of which the knowledge of an expert is widely involved and the inspections performed manually are not only time-consuming and labor-intensive but also prone to human error especially at the initial stages of the disease when the symptoms are extremely slight or even absent. Consequently, a few studies have been done on the use of computer vision, and machine learning to automate the process of diagnosing plant disease with encouraging outcomes in the accuracy and the level of research.

The author [1] suggested the transfer learning methods of the tea leaf disease via (TSCODE). The sample dataset of TLB (Tea Leaf Blight) was also small and used by the author. The author suggested a data Transfer learning (TSCODE) detecting head, Triplet Attention in E-ELAN, and a Wasserstein loss function. The highest 92.2% accuracy was obtained with this model. [2]. The author suggested a Machine learning technique to identify tea leaf disease. The authors applied their personal gathered information. There were two models that the author suggested and then subjected to the Weighted Box Fusion(WBF) algorithm to enhance better detection. The techniques of the deep-learning algorithms of tea disease proposed by an author, were tested on a high-quality dataset of tea diseases, such as tea anthracnose, tea leaf blight, tea grey blight, and Pseudocercospora theae founded on the images taken in different natural conditions in a year and obtained the average accuracy of 79.3%. [3] The scholar suggested that deep-learning algorithms were used. This model got the greatest 94% accuracy.

The author suggested the Deep CNN Model to detect and classify tea leaf diseases. This author employed their gathered data. The author introduced A Deep Convolutional Neural Network (CNN) approach. This mode was the most accurate with 99.10%.[5] The author suggested machine-learning methods of tea leaf disease. The author referred to rain and tested several machine-learning models to classify diseases. The author suggested random forest (RF), Support Vector Classifier (SVC), Extra Tree Classifier (ETC), Decision Tree (DT), XGBoost (XGB), and Convolutional Neural Network (CNN).

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Their results were contrasted to come up with the most performing model. This model had the greatest accuracy of 77.47%. [6]. The author suggested the use of deep learning to classify tea leaf disease. There was no specific dataset mentioned by the author but the versions of data sets that had been used in research on identifying tea diseases. The authors developed various architecture in DL, visualization plans, and measures of performance to determine the accuracy of tea disease detection models. This model evaluated various models but failed to identify precise values of accuracy. [7]. The author came up with MergeModel, a multi-convolutional neural network (CNN) coupled with the diseased leaf segmentation and a weight initialisation strategy to enhance the detection of tea leaf diseases. The writer worked with a small sample of diseased tea leaf pictures. To aid the model in an early training to concentrate on important features of the disease, the author suggested a method of Weight initialization. The MergeModel was successful in categorizing tea white scab, tea leaf blight, tea red scab and tea sooty mold and provided more accuracy in small sample environments than the current techniques. [8]. The author introduced a hybrid system whereby modified state-of-the-art (SOTA) deep learning models are used in conjunction with feature selection and machine learning (ML) classifiers in the accurate detection of four types of tea leaf diseases. The dataset that was used by the author was not clearly stated, but it consisted of diseased tea leaf images that were to be classified. The author came up with a deep learning model of tea leaf diseases. The overall accuracy of the proposed method was 99.5%. [9]. The author made transfer learning methods of tea leaf disease. The author employed a large set of data of healthy and diseased tea leaf images to train and evaluate. The author came up with three hybrid deep learning models. The paper has not mentioned specific values of accuracy but has pointed out the effectiveness of capsule of deep learning in the early detection of diseases, which help improve disease management and improve tea production.

The methods of deep-learning were suggested by the author to tea leaf disease. The dataset used by the author was RGB and hyperspectral images of the tea leaves with tea coal disease. The author suggested that WT-ResNet18 was the best model to use in RGB imaging, and CARS-LSTM in hyperspectral imaging. The greatest 95% accuracy was obtained using this model. [11]. The author put forward the federated learning based on convolutional neural networks (CNNs) in order to classify the methods of tea leaf disease. The authors utilized their personal gathered data. Federated learning and federated averaging algorithm by the author were applied to combine the local data insights into a global model, which did not violate the privacy and also the performance of the model was measured in terms of precision, recall, F1-score, accuracy, and analysis of the macro, micro, and weighted averages data across different classes of disease severity. The model results showed that the model is able to deal with different class distributions and instances and show high accuracy with respect to different dataset. [12]. The author came up with an Information Entropy Masked Vision Transformer (IEM-ViT) architecture to swiftly and precisely identify tea diseases. The research of the author identified seven tea disease types, but it did not specify the dataset that was utilized. The author came up with an IEM-ViT model that uses a masked auto encoder (MAE) having an asymmetric encoder-decoder framework. The accuracy of this model was 93.78.

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Table 2.1: Summary of the reviewd Literature

Author (s)	Year	Title	Methodology	Major Insights
Mohanty et al. [1]	2016	Deep Learning-based Image-based Detection of plant diseases.	CNNs were trained on 54306 images of 14 crop species.	Obtained an accuracy 99% and above; works well with visible disease symptoms.
Ferentinos [2]	2018	Deep Learning Plants Disease Detection and Diagnosis.	Transfer learning CNNs (AlexNet, VGG,GoogleNet).	High classification accuracy achieved; demonstrates that transfer learning can be used in agriculture.
Tan & Le [3]	2019	EfficientNet: Re-Tuning Model Scaling to Convolutional Neural Networks.	Safer Built EfficientNet architecture on top of scaling compounds.	EfficientNet models are more effective than the earlier CNNs and they are computationally efficient.
Liu et al. [4]	2021	Identification of Apple Leaf Disease Relying on EfficientNet.	Used EfficientNet to classify apples leaf diseases.	High precision and strength of agricultural image classification.
Zhang et al. [5]	2020	Ensemble Classification of Tomato Leaf Disease.	Stacking of several CNN models.	Performed better than single models; better generalization and strength.
Sharma et al. [6]	2020	ELA use in Image integrity verification in Agriculture.	Preprocessing via the Used Error Level Analysis (ELA).	Assisted with finding concealed image artifacts; better detection ability.
Sanyal & Bhattacharya [7]	2022	The CNN-based Fungal Disease Detection in Tea Leaves.	Trained CNN on tea leaf.	Good accuracy, poor generalization.
Islam et al. [8]	2019	Deep Neural Networks Transfer Learning with Rice Disease Recognition.	Ready-made models on the images of rice disease.	Demonstrated better accuracy on small samples of the training.
Singh et al. [9]	2021	Mobile AI to Detection Disease of Crops in Real Time.	CNN deployed on the mobile to diagnose the field.	Capable of real-time detection in the mobile device; handy to low-resource farmers.

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Khan et al. [10]	2020	Ordinal Classification of severity of crop disease.	Applied deep learning ordinal classification.	Better classification based on the levels of disease severity.

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2.3 Gap Analysis

Although technology in agriculture has progressed greatly, they still have a problem of early diagnosis of tea leaf disease especially because of the absence of material symptoms during the early stages of infection. Although various researchers have applied conventional machine learning algorithms and image processing to detect plant diseases, their results are usually constrained by scalability, accuracy, and lack of resistance to changes in the environmental factors (e.g., lighting, angle, or background noise in field photos). The available literature has been more of general plant disease classifications with relatively little work done in tea leaf disease classification given the large effect of the disease in world tea production. In addition, most of the past models have been trained using small datasets or without thorough preprocessing and augmentation plans, thus creating problems such as overfitting and failure to generalize in practice.

One more interesting gap to be identified is lack of research comparing the regular classification with ordinal classification because many diseases have an ordinal course (e.g., healthy - mild - moderate -severe). The use of ordinal classification in the given study is a new method of filling this gap and developing more precise and sensitive disease severity measure.

Table 2.2: Research Gap Analysis Table

Features / Studies	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Large & diverse dataset used	No	No	Yes	No	No	No	No	No
Covers multiple diseases	No	No	Yes	No	No	No	Yes	Yes
High accuracy (>90%)	Yes	No	Yes	Yes	No	No	Yes	Yes
Dataset clearly specified	Yes	Yes	Yes	Yes	Yes	No	Yes	No
Risk of overfitting	Yes	No	No	Yes	No	No	No	Yes
Advanced techniques	Yes	No	No	No	No	Yes	Yes	Yes
Generalizability (real-world tested)	No	No	Yes	No	No	No	No	No

2.4 Summary

Tea leaf disease is a significant cause of tea production and usually, remains unnoticed at the initial stages before a large percentage of crop is lost. The proposed study presents the opportunity to detect tea leaf disease with the help of automated methods and deep learning, transfer learning, and ensemble. Preprocessing and massive augmentation (resizing, rescaling, flipping, rotation, zooming, and contrast adjustment) of the dataset were used with Error Level Analysis (ELA) to boost pattern recognition. Transfer learning was also used with pre-trained models (EfficientNetB0 and EfficientNetV2B1), and ensemble models (CNN + EfficientNetB0 and CNN + EfficientNetV2B1). Both regular and ordinal classification were experimented. Findings indicated that the ordinal classification using EfficientNetB0 had the best accuracy of 91.91 and CNN + EfficientNetB0 had 89.04. These results support the possibility of deep learning methods to give farmers and agronomists cost-effective and accurate early disease and disease classification tools in tea leaf.

Chapter 3

Research Methodology

3.1 Methodology

This chapter describes the methodology used in the project, including requirement analysis, system design, detailed methods, and the overall project plan.

3.1.1 Overview

Here we have used the deep-learning framework for Tea Leaf disease.Here we have done the transfer learning in two stages.One is EfficientNetB0 and EfficientNetV2B1.For image classification we use ordinal and regular classification. We use seven types of classes in the data set. Which are very mildly demented, mildly demented, non-demented and moderately demented. Our model is able to classify these four classes accurately.A brief working scenario is shown in this below

3.1.2 Proposed Methodology/ System Design

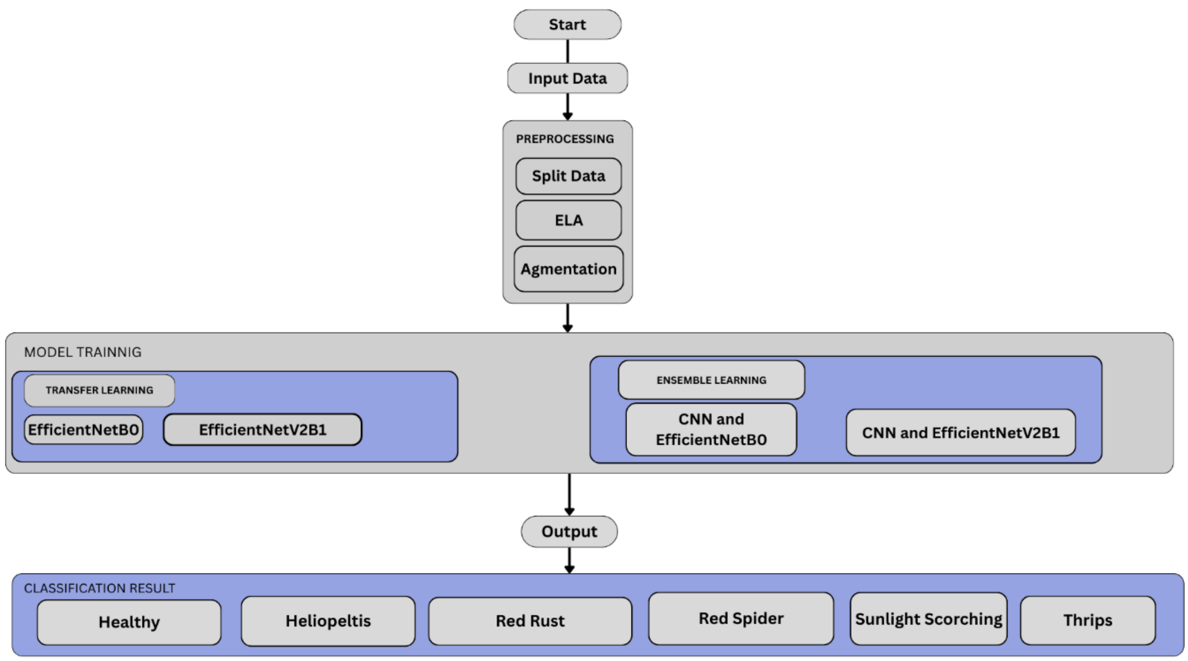

Figure 3.1: Proposed Methodology

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3.1.3 Functional and Nonfunctional Requirements

Functional requirements are statements of the functionality of the system they specify the essential functions, services and behaviors of the system under given circumstances. Within the tea leaf disease detection system, they are the acceptance of image inputs, preprocessing (resizing, rescaling, flipping, rotation, zooming, contrast, etc.), the application of the deep learning models (EfficientNetB0, EfficientNetV2B1, CNN ensembles, etc.), and both ordinal and regular classification methods.

Nonfunctional requirements explain the way the system would work -they concentrate on quality characteristics that affect the user experience and system design and not on specific behavior. In the case of the tea leaf disease detection system, they are the performance efficiency, which is generating predictions in a few seconds, and scalability, enabling more than one user to access the system at the same time.

3.2 Detailed Methodology and Design

The data was made ready and pre-treated in order to provide consistency and enhance the quality of the input data. This dataset has been preprocessed and the proposed model is trained based on this data and then a testing process was carried out to test the performance.

3.2.1 Dataset

The data set used in the study was collected from the Mendeley Website. The study used" Tea Leaf Diseases Dataset" [25] from the. There are six types of classes in the data set. They are: Healthy, Helopeltis, Red Rust, Red Spider, Sunlight Scorching, and Thrips. First, the data was prepared and pre-processed. This model was trained with the data set. Then it was tested. Some sample images from the set used in this study are shown in Figure 3.2 below:

		
Healthy	**Heliopolis**	**Red Rust**

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Red Spider	**Sunlight Scorching**	**Thrips**

Figure 3.2: Samples of dataset images

3.2.2 Analysis Techniques

The data set was used to identify tea leaf diseases and had six classes: Healthy, Helopeltis, Red Rust,Red Spider,Sunlight Scorching and Thrips. Figure 3.5 shows the each class bar chart.

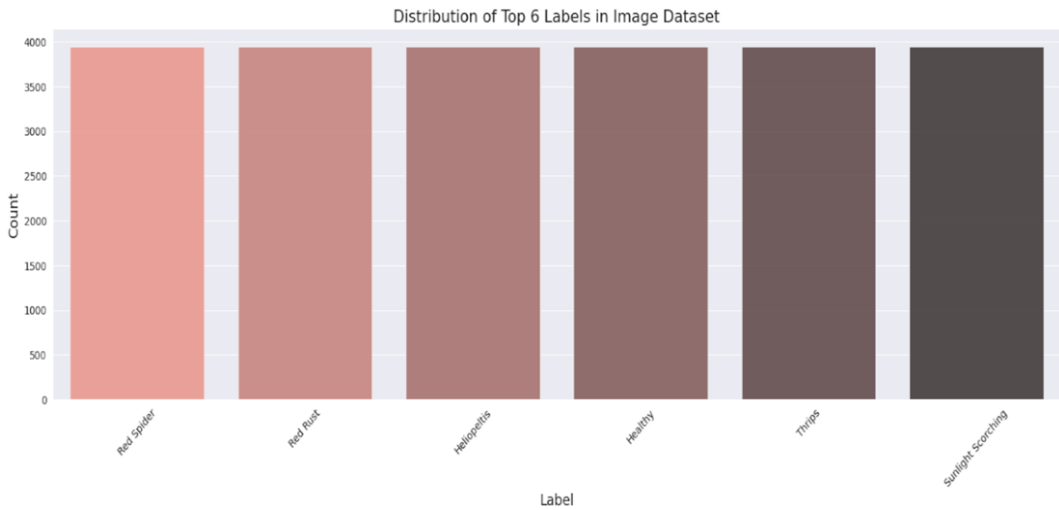

Figure 3.3: Per class bar chart

From Figure 3.3 we can see that each class has an equal amount of data. If there were not equal amounts, then it would be very challenging for the model. The dataset was pre-processed. We used a total number of 23,676 images for the model. We took 3,946 images in each class to train the model. Each image dimension is 800 x 800.

To improve the performance of the model, we performed an Error Level Analysis (ELA). Using ELA, we were able to correctly identify each part of the image. This can basically detect if any part of the image is missing. Figure 4 below shows how ELA is working for each image. Figure 3.4 shows the error level analysis of the dataset.

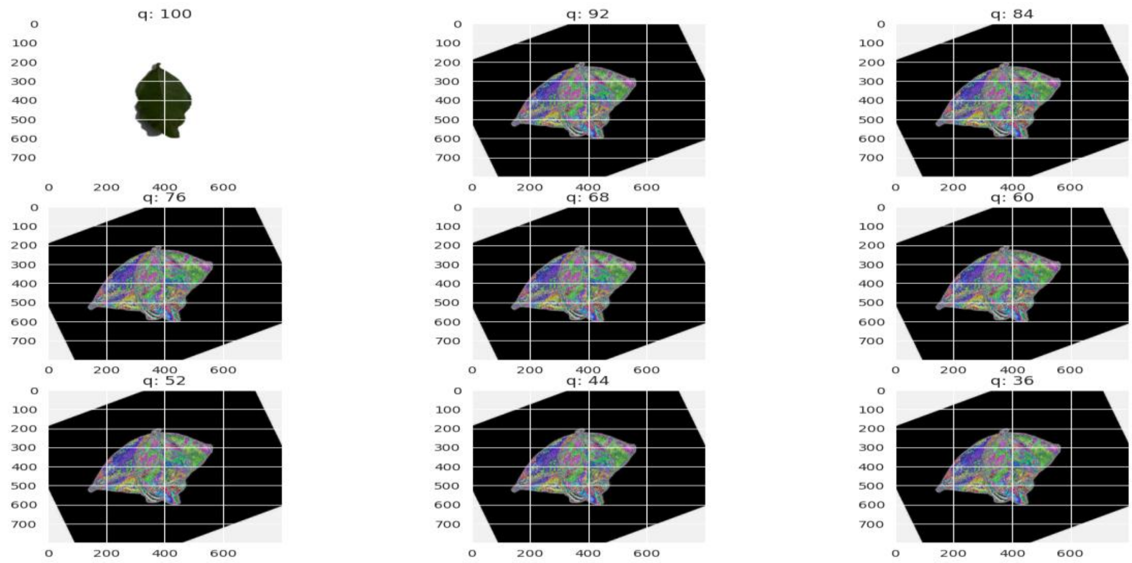

Figure 3.4: Error-Level Evaluation of the Dataset

3.2.3 Image Augmentation

The dataset was preprocessed. Then we preprocessed the data set again. We used various enhancement methods to prevent overfitting to improve the performance of the model. We have adopted many types of enhancement methods. Such as rescaling, resizing, flipping, zooming, contrasting, and rotation. The image after completing the augmentation is shown below in Figure 3.5

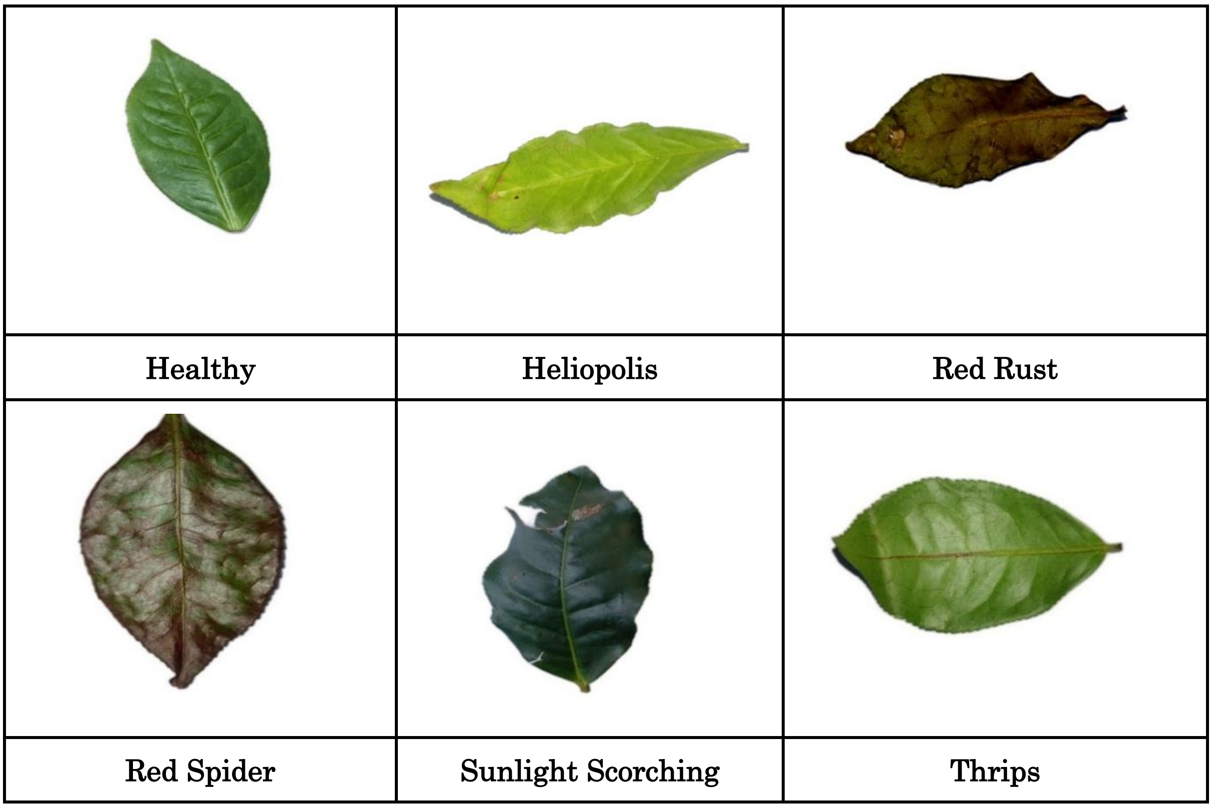

Figure 3.5: Augmented image examples

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3.2.4 Experimental Setup

Table 3.1. The experimental setup of the tested architecture is:

Parameters	Value
Activation	Relu, Softmax
Optimizer	Adam, Adamax
Learning Rate	0.0001
Entropy	Categorical-crossentropy
metrics	Accuracy
Epoch	50
Patience	5
Batch Size	32

3.2.5 Model Selection

At this stage we have adopted a deep learning method to detect tea leaf diseases. Because it can efficiently detect and classify tea leaf diseases. We have used two types of methods here one is transfer learning and other is assembly learning. For transfer learning, we used three types of architectures, which are EfficientNetB0 and EfficientNetV2B1. Now we have divided the three architectures of transfer learning into two types of classification, which are ordinal and regular classification. On the other hand, for ensemble learning, we used two types of architectures, which are CNN + EfficientNetB0 and CNN + EfficientNetV2B1. Again, we have divided the two ensemble learning architectures into two more types of classification, which are ordinal and regular classification. Each of these architectures was chosen for their good results in easily detecting tea leaf diseases. But we changed different parts of the model and showed the performance, especially adding some new layers, and we also changed the optimizer. Then we used SoftMax as the output layer which can classify different diseases.

3.2.6 Model Training and Evaluation

The aim of such models is to reach high accuracy due to the possibility to do fewer parameters and computational work. The model was first optimized or preprocessed to train it. Once the classes had been balanced correctly, we split the data set into three, that is, training, testing and validation sets.We adjusted the patient in the model to three. That is, the model will be executed until the number of model validation losses becomes five times greater. Our batch size was 16 on which we realized that the model is very time consuming to run and model is overfitting, hence we decided to use batch size 32. The training parameters such as learning rate and optimizer were used to tune the batch size. The performance matrix is used in every architecture. Adagrad and SGD were also applied, but could not provide good results, thus we applied Adam with a learning rate of 0.0001. The classification performance was assessed using precision, loss, recall, f1-score, and model performance matrix in the test set.

3.3 Project Plan

Any project can be described as effective planning. The period provided to this project was one year. So, the careful planning was a crucial part to be guaranteed in achieving the completion of this project. The project schedule can be summarized as below:

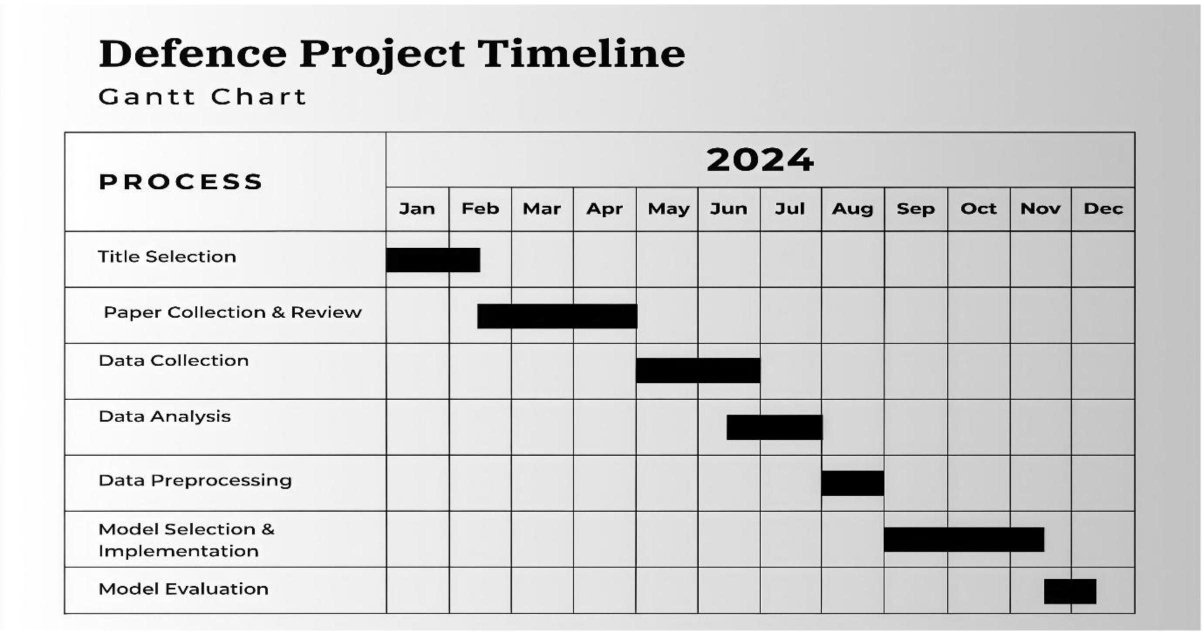


Figure 3.8 Project Timeline Gantt Chart

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.

3.5 Summary

The current study aims at developing the deep learning methods to detect tea leaf disease at an early stage, a major contributor to crop loss. Preprocessing of the dataset was done through augmentation techniques and analyzed by the use of Error Level Analysis. Several models of transfer learning, such as EfficientNetB0 and EfficientNetV2B1 as well as ensemble models between CNN and EfficientNetB0/V2B1 were used in ordinal and standard classification tasks. The model of EfficientNetB0 was the most efficient, and its accuracy stood at 91.91. CNN + EfficientNetB0 was the model that produced the highest accuracy of 89.04. The models have been created to help farmers and agronomists in successful diagnosis and identification of tea leaf diseases.

Chapter 4

Implementation and Results

4.1 Environment Setup

In the experimental setup, the study was carried out on cloud-hosted services that are offered by Google Colab and Kaggle Notebooks, and which offer a free GPUs/TPUs environment suitable to carry out deep learning tasks. The reason behind the choice of these platforms is because they are easy to use, can be scaled, and they have in-built support of some of the most popular machine learning libraries like TensorFlow, Keras, and PyTorch. Python 3 was configured and all the required dependencies were installed using pip and pre-configured packages that were provided in the runtime. These environments were used to perform data preprocessing, model training, and evaluation, which is reproducible and can be easily collaborated with. Furthermore, the computational cost and training time were greatly decreased with the usage of the GPU acceleration, which provided it as an effective option to work with large-scale datasets.

4.2 Performance Matrix

We used performance matrix on the data to determine the effectiveness of the models in identifying correct and incorrect predictions. This matrix enables one to know whether the model was in the right position to pick up actual values (true) or falsely classified (false). The key components are:

- **True Positive (TP):** The model correctly predicted positive class.
- **True Negative (TN):** The model correctly predicted negative class.
- **False Positive (FP):** The model fails to declare a negative sample as positive.
- **False Negative (FN):** The model wrongly identifies a positive sample as negative.

- **Accuracy:** Accuracy indicates how well the model performs. Equation 1 is:

$$Accuracy = \frac{TP + TN}{(TP + TN + FN + FP)} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (1)$$

- **Precision:** Precision gives an idea of how many positive predictions the model made. Equation 2 **is:**

$$Precision = \frac{TP}{(TP + FP)} \quad (2)$$

- **Recall:** Recall identifies all the true positive cases the model has. Equation 3 is:

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

- **F-Score:** The F1-score gives a good idea of the model's performance, especially for unbalanced data sets. Equation 4 is:

``

$$F1 - score = \frac{2 * ((Precision \ * Recall)}{(Precision \ + Recall))} \tag{4}$$

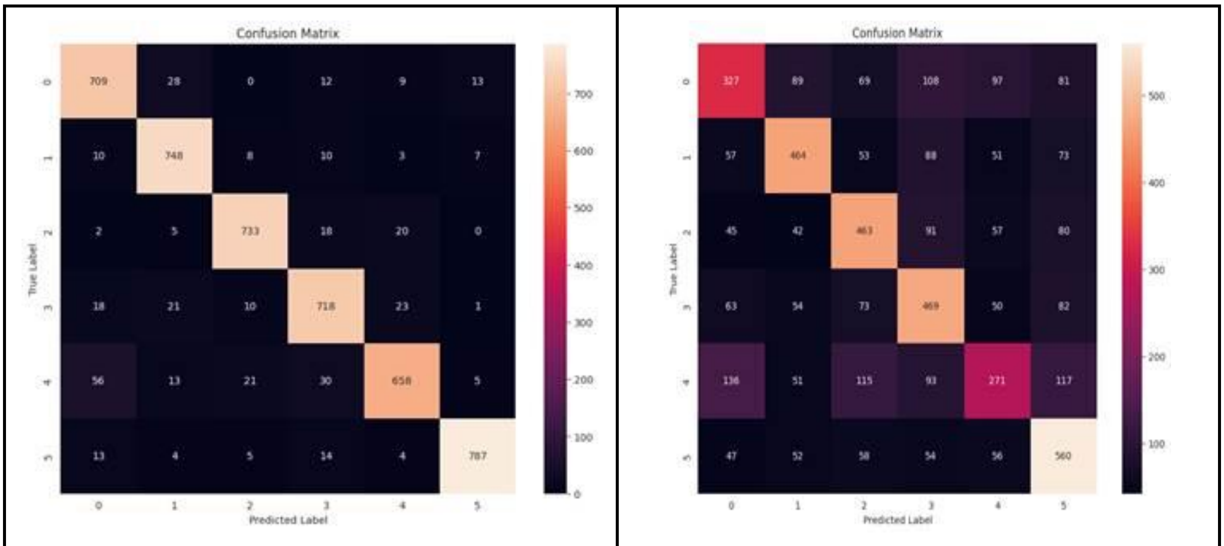
Furthermore, a loss curve is employed to evaluate how well the model performs.

4.3 Experiment 1- Performance of Transfer Learning

We employed three transfer learning models: EfficientNetB0, EfficientNetV2B1, and CNN. These architectures were tested under two classification approaches—ordinal classification and regular classification. As shown in Table 4.1, EfficientNetB0 achieved the highest accuracy of 91.91% in ordinal classification, followed by EfficientNetV2B1 with 99.93% and CNN with 90.75%. On the other hand, EfficientNetB0 recorded the lowest accuracy when applied to regular classification. Table 4.1shows the accuracy of transfer learning models for tea leaf disease detection.

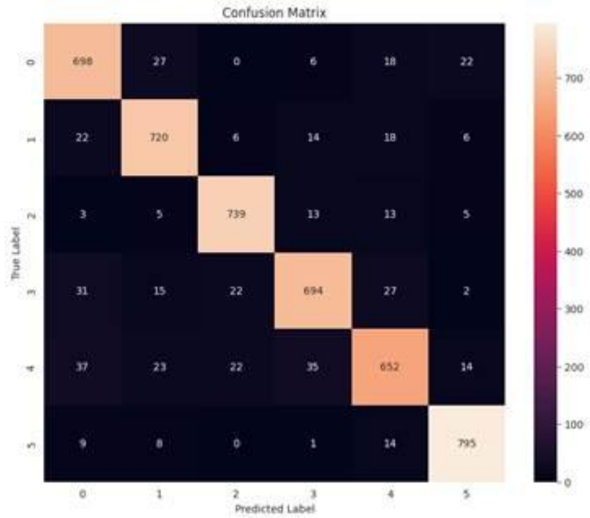
Table 4.1: Accuracy of transfer learning models for tea leaf disease detection.

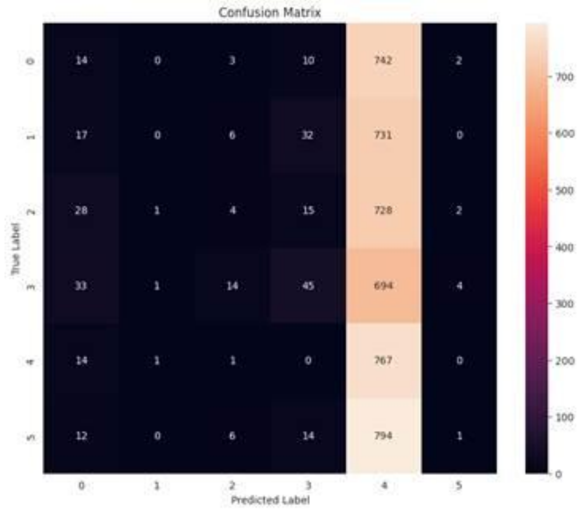
Architecture		Model Accuracy
EfficientNetB0	Ordinal classification	91.91%
	Regular classification	53.93%
Basic + EfficientNetV2B1	Ordinal classification	90.75%
	Regular classification	17.55%
Basic CNN	Ordinal classification	68.03%
	Regular classification	48.18%
Basic + EfficientNetB0	Ordinal classification	89.04%
	Regular classification	18.50%



Ordinal classification	Regular classification

EfficientNetB0

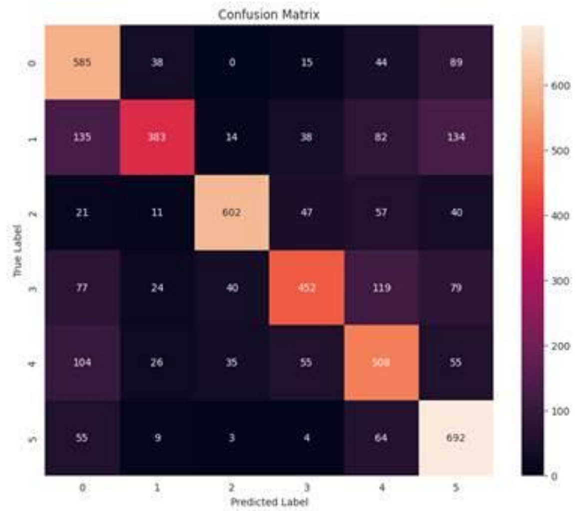


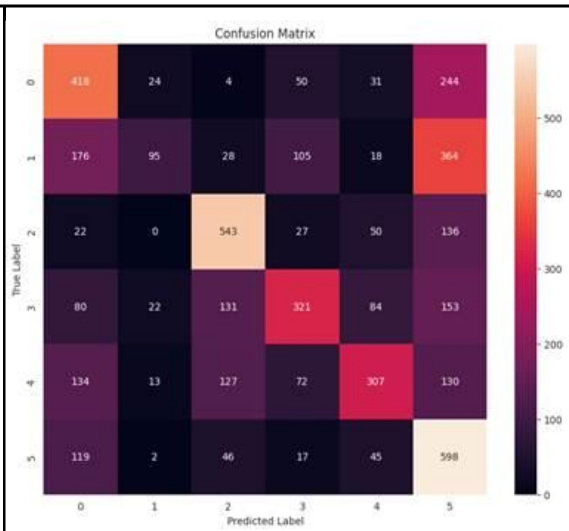


Ordinal classification

Regular classification

Basic & EfficientNetV2B1





Ordinal classification

Regular classification

Basic CNN

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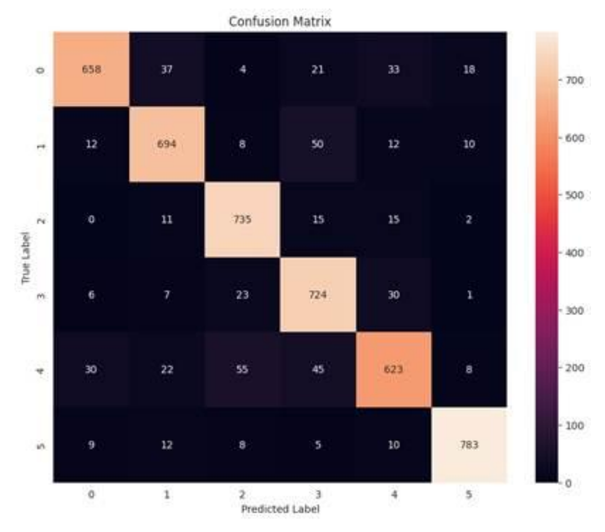
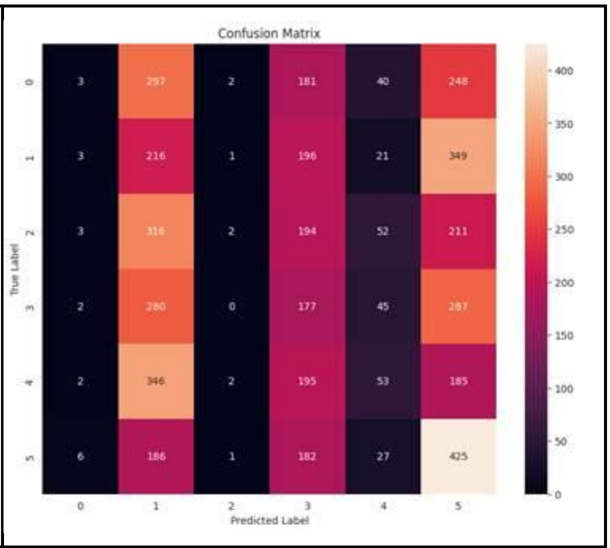
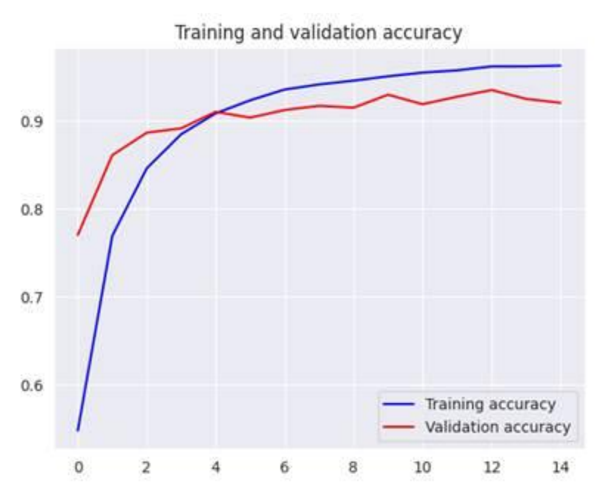


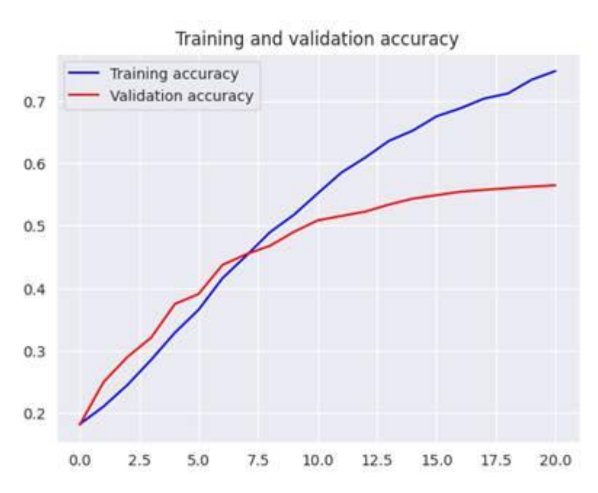


Ordinal classification	Regular classification
Basic & EfficientNetB0 for Combined	

Figure 4.1: Six confusion matrices of transfer learning.

The confusion matrices of all the models appear in figure 4.1. Two kinds of classification are contained in EfficientNetB0 namely, ordinal classification and regular classification. On the same note, both regular classification and ordinal classification are offered in the case of EfficientNetV2B1. Similarly, two kinds of classification can also be found in CNN. Based on the confusion matrices above, we can get a grasp of the perceptions of each model.





Ordinal classification	Regular classification
EfficientNetB0	

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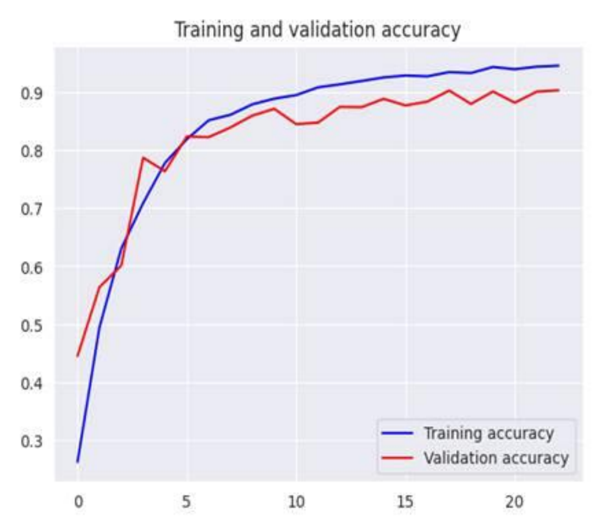
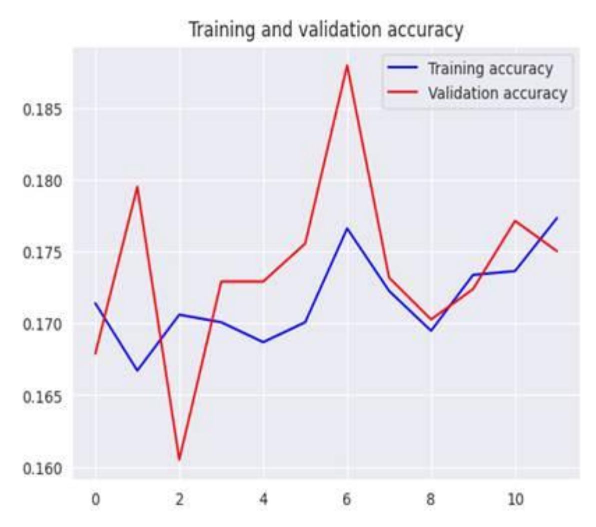
<tr><td>
</td><td>
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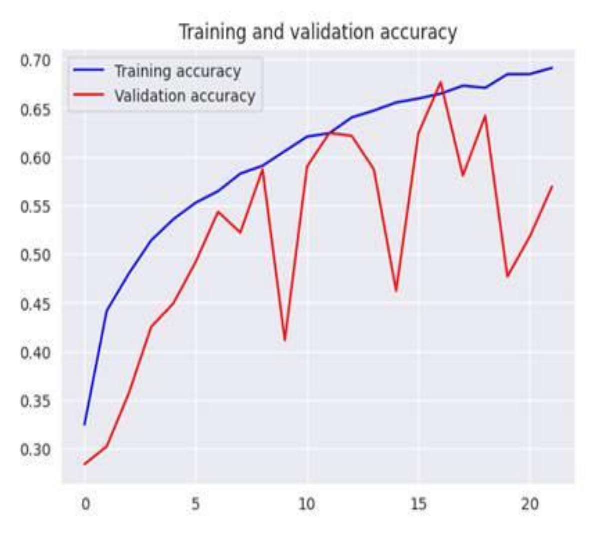
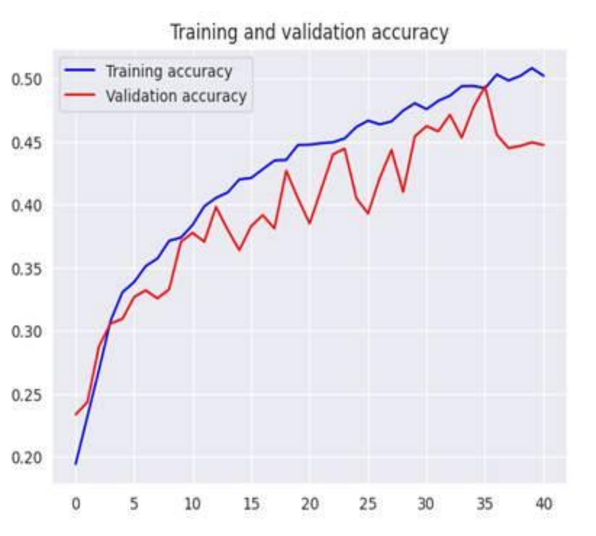
<tr><td>
</td><td>
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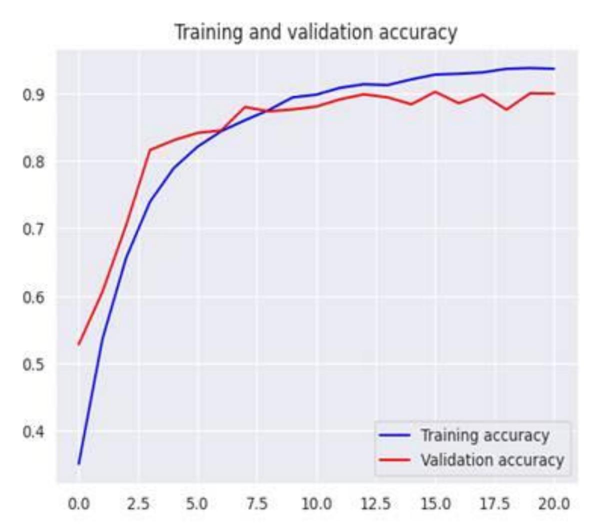
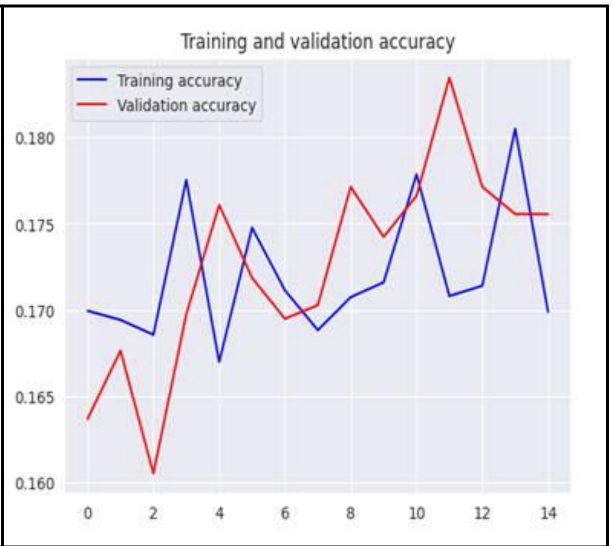
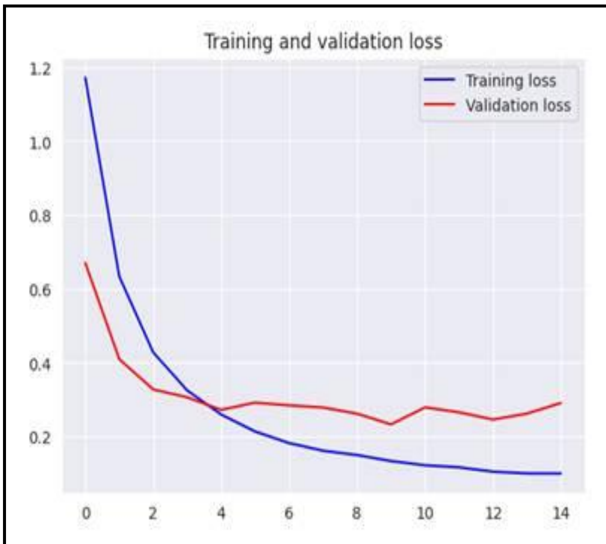


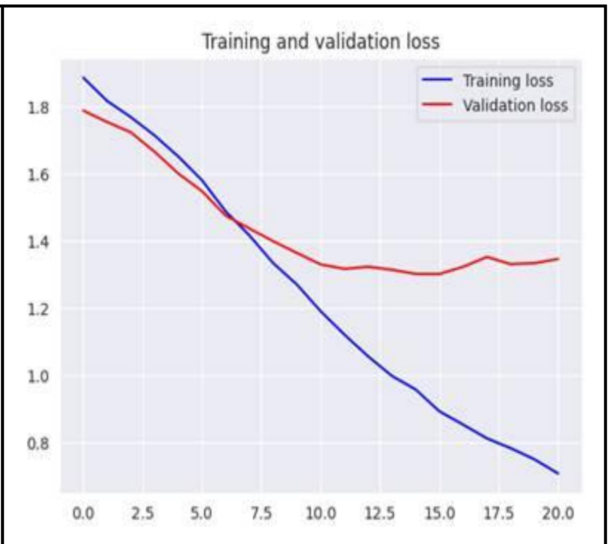


Ordinal classification	Regular classification
Basic & EfficientNetB0 for Combined	

Figure 4.2: Training & validation accuracy

The figure shows the training and validation accuracy of the ordinal and regular classification methods with the aid of Basic CNN. With ordinal classification, the model experiences a gradual increase in accuracy with the training accuracy approaching 0.95 and validation accuracy more or less converging at 0.92. This implies that the model has a low level of overfitting and is a good model of generalization because both curves would tend to follow a common trend. In general, it can be pointed out that ordinal classification method is much more successful than standard classification, and the fact that the Basic CNN is combined with the EfficientNetB0 suggests possible performance enhancement.





Ordinal classification	Regular classification
EfficientNetB0	

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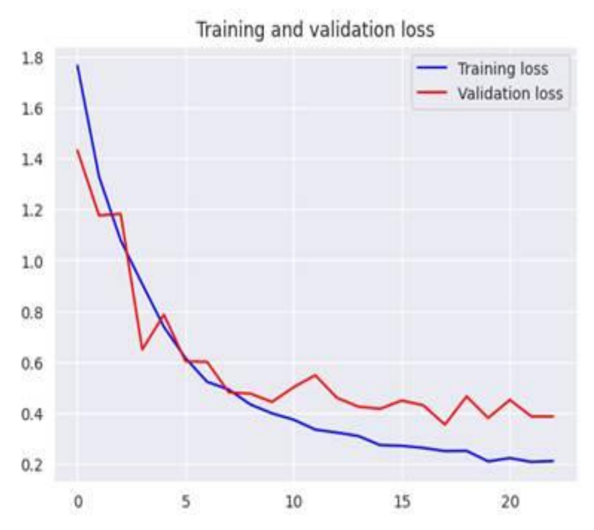
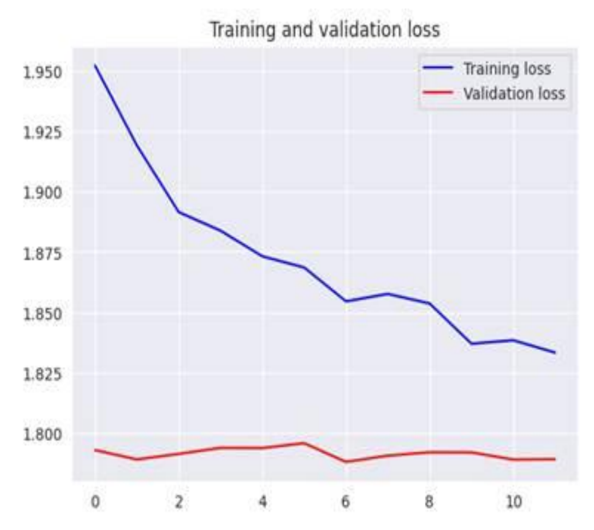
<tr><td>
</td><td>
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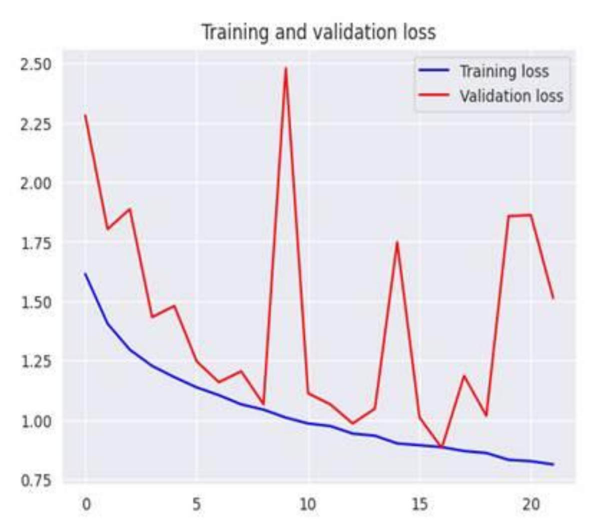
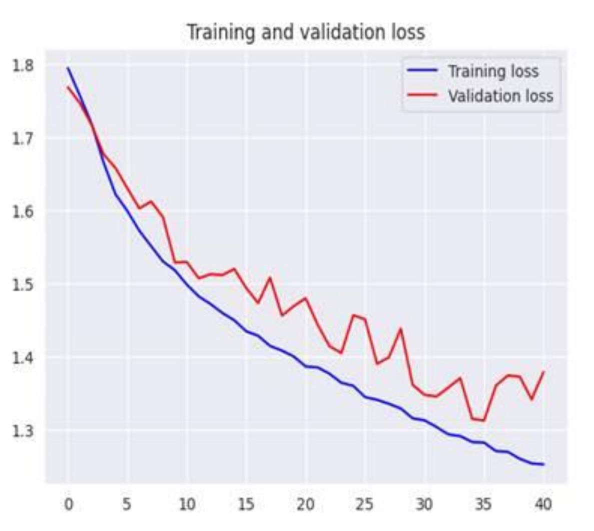
<tr><td>Ordinal classification</td><td>Regular classification</td></tr>
<tr><td colspan="2">Basic & EfficientNetV2B1</td></tr>
<tr><td>
</td><td>
</td></tr>
<tr><td>Ordinal classification</td><td>Regular classification</td></tr>
<tr><td colspan="2">Basic CNN</td></tr>
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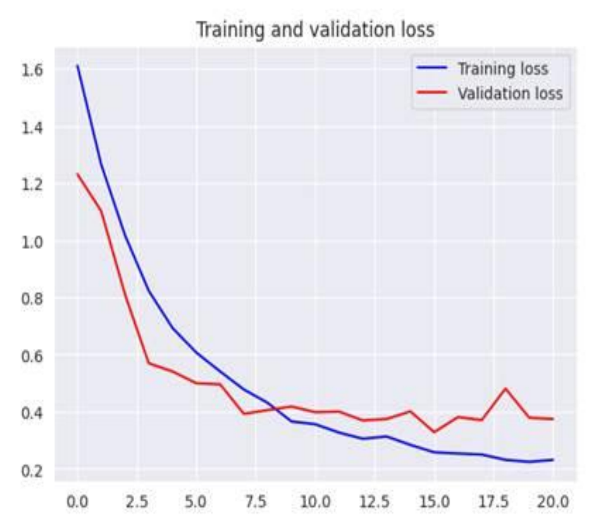

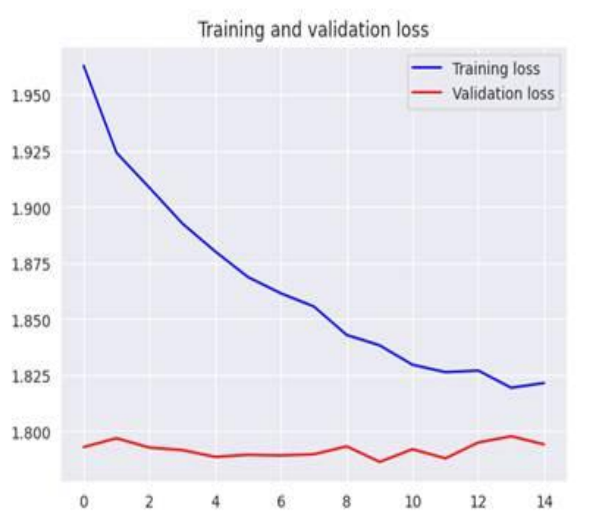

Ordinal classification	Regular classification
Basic & EfficientNetB0 for Combined	

Figure 4.3: Training & validation losses

Figure 4.3 is a figure that shows the training and validation loss curves of Basic and EfficientNetB0 models using Combined data, where Ordinal classification (left) and Regular classification (right) are studied. The training and validation losses in the Ordinal classification plot (left) declines extensively and steadily with the increase in epochs, which means that learning is stable and that generalization is improved. Loss on validation is near to training loss meaning that the model is not overfitting.In general, ordinal classification method seems to enhance learning behavior and performance in this case.

4.4 Results and Discussion

This has been transferred and accomplished with two advanced methods of deep learning. These frameworks were also proved to be most helpful in identification and classification of the tea leaf diseases in terms of the images.

Table 4.2: Comparative analysis of all model

Model	Ordinal classification	Regular classification
EfficientNetB0	91.91%	53.93%
Basic + EfficientNetV2B1	90.75%	17.55%
Basic + EfficientNetB0	89.04%	18.50%

Both ordinal classification and regular classification methods were used to estimate the performance of various deep learning models. Table 4.1 summarizes the obtained results of EfficientNetB0 and the EfficientNetV2B1 frameworks, as well as the results of the hybrid frameworks. The highest performance on ordinal classification was achieved using EfficientNetB0 with loss and accuracy 91.91 that illustrates the effectiveness of the model to approach the ordinal relationship between the disease categories. Conversely, the accuracy of its standard classification was relatively lower at 53.93 which may indicate that ordinal classification offers an orderlier classifying benefit to prediction of severity of the disease.

The basic architecture with EfficientNetV2B1 returned 90.75% accuracy in ordinal classification, similar to EfficientNetB0, however, its performance declined drastically in regular classification (17.55%). On the same note, the combined ordinal classification and regular classification of Basic and EfficientNetB0 achieved 89.04% and 18.50% respectively. Such findings suggest that regular classification does not reproduce the accuracy of the ordinal classification in all models, whereas the latter clearly provides a higher accuracy. In general, the findings demonstrate the efficiency of transfer learning and ensemble methods in increasing the accuracy of classification. The high performance of the ordinal classification indicates that the approach fits well in problems, in which the stages or the severities of diseases have a natural progression, as in the tea leaf disease detection.

4.5 Summary

In this study, the performance of various deep learning models was compared when they were used to detect tea leaf disease by use of ordinal and regular classification. Findings indicate that ordinal classification always obtained high measures of accuracy in all the models and EfficientNetB0 was the highest at 91.91%. Conversely, the normal classification generated much lower accuracies, with best 53.93% using EfficientNetB0. The results confirm that the ordinal classification is more efficient in capturing the level of disease severity with the additional improvement of the model performance by the transfer learning and ensemble methods.

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Chapter 5

Engineering Standards and Design Challenges

5.1 Compliance with the Standards

The project is in line with the necessary software and hardware requirements to make the implementation and performance of the software and hardware run smoothly. All experiments were done in python 3.9 along with TensorFlow through Jupyter/Google Colab that complies with the established software requirements. In the same way, the environment on which the system was implemented satisfied the hardware requirements; it was run on Windows 10, 8 GB RAM, and 512 GB storage.

5.1.1 Software Standards

The required software for this project:

- Google Chrome or Microsoft Edge
- Python 3.9
- Tensor flow
- Jupiter or Google Colab or kaggle

5.1.2 Hardware Standards

The required software for this project:

- Windows 10 operating system
- Hard Disk 512 GB
- 8 GB RAM

5.2 Impact on Society, Environment and Sustainability

Early and automatic tea leaf disease detection increases the income security level of farmers, minimizes the risks to human health on using pesticides, and improves the overall community wellbeing. On the environmental front, it reduces the unnecessary use of chemicals that leads to better health in the environment. As far as sustainability is concerned, it can guarantee long-term productivity of crops, resource efficiency, and sustainable farming practices.

5.2.1 Impact on Life

Early diagnosis of tea leaf disease has a major impact on livelihood of tea farmers and workers. Reduction of crop loss will boost food security and food availability, and decrease of pesticide use will reduce health risks to agricultural laborers and the community around them. In addition, automation of disease detection reduces the amount of labor that needs to be done by an individual, thus allowing the farmers to focus on other critical duties and thus increasing efficiency and welfare.

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5.2.2 Impact on Society & Environment

Timely detection of tea leaf disease has a great impact in the quality of life of tea farmers and their laborers. Reduced crop loss improves income security and food availability, and decreased pesticide use reduces health risk among agricultural workers and the communities living near the homes of agricultural workers. Further, automation of detection of diseases reduces the labor force and farmers are able to focus on other essential tasks thus resulting to improved efficiency and wellbeing.

5.2.3 Ethical Aspects

Deep learning in the process of identifying diseases in tea leaves comprises a number of ethical considerations. Data privacy plays a crucial role to adhere to in collecting and using images on the fields of farmers. Also worth considering is the equitable access to this technology by making both the small-scale and resource-constrained farmers have a share in the larger plantations. Openness about decision making process of the models is essential towards inculcating trust in users. The responsible use of this technology is promoted by the ethical use of the technology, which fosters fairness, accountability and responsible use of AI in agriculture.

5.2.4 Sustainability Plan

The sustainability plan of the deep learning methods applied to tea leaf diseases detection focuses on the benefits in long term to the agriculture, environment and people. The system helps in reducing crop losses by enabling early and accurate detection of the diseases, hence providing farmers with economic stability as well as the ability to have a constant supply of tea. Moreover, in this way, there is reduced use of chemical pesticides indiscriminately, preventing unfavorable effects on the health of the soil, preserving the biodiversity of the area, and reducing the pollution of the environment. A system can also be updated regularly with new disease information to keep it sustainable to new plant diseases or change in environmental conditions. Training farmers and agronomists in the area on the use of the technology contributes to knowledge transfer and capacity building and thus the solution will become available to even the small-scale plantations. Also, it is possible to connect the system to the mobile applications or cloud platforms to enable it to be adopted broadly and be used over the long run. Overall, the sustainability plan will ensure that this AI-based solution will facilitate environmentally sustainable agricultural practices, financial stability, and social wellbeing, which will create a scaled-up approach to sustainable farming in tea plantations.

5.3 Project Management and Financial Analysis

- Project Timeline:

Phase 1: Research and planning of the project (1 week)
Phase 2: Collection of Reference Paper (1-2 weeks)
Phase 3: Paper Review (1-2 weeks)
Phase 4: Data Collection for work (1-2 weeks)
Phase 5: Data Analysis (1-2 weeks)
Phase 6: Data Preprocessing (1-2 weeks)
Phase 7: Model Implement (1-2 weeks)
Phase 8: Model Evaluation (1-2 weeks)
Phase 9: Prototype Design (1 weeks)

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Phase 10: Front End Development (1-2 weeks)

Phase 11: Deployment and Testing (1-2 weeks)

- Resource & Planning system:

A. Equipment & Tools use:

  - Development & Testing Servers
  - Collaboration Tools System
  - Version control System
  - Testing Tools Management

B. Software and Technologies:

- Front-End Uses:(HTML, CSS, JavaScript and React)
- Back-End Uses: (Django, Node.js and Flask)
- Server Hosting: (Azure, AWS or Google Cloud)
- Security Software and SSL Certificates

5.4 Complex Engineering Problem

5.4.1 Complex Problem Solving

Table 5.2: Mapping with complex problem solving.

EP1 Dept 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
✓		✓		✓	✓	

Mapping with Knowledge Profile

Table 5.3: Mapping with knowledge Profile.

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

``

5.4.1.1 Justify EP Attributes Mapping

- **EP1 - Depth of Knowledge Required:**

  There is EP1 through K3, K4, K5, K6, and K8 demonstrated in this project. The EP1 project uses the best deep learning models with learning methods that demand the firm command of the medical imaging data pre-processing and neural network architecture.

- **EP2 - Range of Conflicting Requirements:**

  EP2 Accuracy versus computational efficiency The trade off between accuracy and computation efficiency also needs a solution and data set imbalance and overfitting present conflicting requirements.

- **EP3 - Depth of Analysis:**

  The analysis of EP3 was conducted at detail, pre-processing and comparative performance based on eight single model and hybrid ensemble model development.

- **EP4 - Familiarity of Issues:**

  EP4 was an overfitting optimizer choice and batch size fine-tuning problem, but could not be afforded in the medical field.

- **EP5 - Extent of Applicable Codes:**

  EP5 is a python, TensorFlow, karas model implementation with a high level of adherence to international standards in medical research.

- **EP6 - Extent of Stake-holder Involvement:**

  EP6 is a system that targets the pathologists, oncologists and healthcare professionals and has also influenced the goals of their demand model.

- **EP7 - Interdependence:**

  The EP7 project unites several areas especially those in medical imaging, computer vision, deep learning, and healthcare application, and demonstrates high interdependency of these fields.

5.4.1.2 Justify Knowledge Profile Mapping:

- **K1 - Natural Science**

  K1 is natural science research on the principles of applied biology and medical science, e.g. cervical cell image analysis.

- **K2 – Mathematics:**

  K2 is mathematics that studies the statistical probability optimization and loss functions applied to training models.

- **K3 - Engineering Fundamentals:**

  K3 is a course in engineering foundations that includes the basics

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of applied computer science and AI, and in particular neural networks, convolutional backpropagation.

- **K4 - Specialist Knowledge:**

  K4 is Specialist Knowledge that is a deep learning method that can also be used in medical image classification.

- **K5 - EngineeringDesign:**

  K5 is an end-to-end diagnostic system with framework model development and integration of ensembles.

- **K6 - EngineeringPractice:**

  K6 Hello Engineering Practice that applies applied solutions to python, TensorFlow, karas, OpenCV, dataset management and evaluation pipeline.

- **K7 – Comprehension:**

  The model performance issue, particularly the overfitting optimizer effects is K7 and corrective measures have been taken and the batch size has been tuned.

- **K8 - Research Literature:**

  K8 is a literature review of cervical cancer detection that is compared to later work and that adopts the most effective models.

5.4.2 Engineering Activities

Table 5.4: Mapping with complex engineering activities.

EA1 Variety of Available Resources	EA2 Depth of interaction	EA3 Invention	EA4 Impact on society and the environment	EA5 Comprehension
✓	✓	✓	✓	✓

Mapping with Complex Engineering Activities

The offered research deals with the problem of tea leaf disease detection by the means of deep learning. This issue can be traced to a number of Complex Engineering Activities (CEAs), as they are presented below:

- **EA1: Range of Resources**
  Various computer aids are used in the study including deep learning systems (TensorFlow/Keras), ready-to-use models (EfficientNetB0, EfficientNetV2B1), and architecture combinations (CNN + EfficientNet). Also, data is augmented and analyzed using Error Level Analysis to increase the variability of the dataset, and the system is able to learn with a limited amount of real world data. The solution

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proves to be efficient in terms of the hardware (GPU-enabled systems) and software (Python, machine learning libraries) integration.

- **EA2: Level of Interaction**
  The analysis is multidisciplinary in nature, and it includes agronomy, computer vision, and artificial intelligence. Agronomists offer a domain of knowledge regarding tea leaf diseases, whereas machine learning engineers offer sophisticated methods of deep learning. The end-users are the farmers who will be benefiting in having a simple detection tool. This interaction on both sides of the agricultural industry and AI makes deployment viable.

- **EA3: Innovation**
  This is an innovative process that involves transfer learning in association with ensemble techniques and examination of ordinal classification in disease recognition- new in the agricultural field. The originality of the methodology is further improved by using Error Level Analysis (ELA) as the means of recognizing the pattern. The strategies are used to lead to high accuracy and strength in disease classification.

- **EA4: Consequences for Society and Environment**
  Timely prevention of tea leaf disease has far reaching implications on the losses of crops hence sustainable tea production and increased yield. The solution addresses food security and rural livelihoods by enabling farmers to use cheap AI solutions. On the environment, it ensures that the use of excessive pesticides is minimized hence, eliminating exposure of harmful chemicals to the ecosystem.

- **EA5: Familiarity**
  Crop disease detection is not a new issue in agricultural research, yet it was proposed that the application of advanced deep learning models, such as Efficient Net and ensemble models, increases the technical complexity of the issue. The study presupposes the knowledge of machine learning, image processing, and agricultural-related data, which is why it could be applied to complex engineering analysis.

5.5 Summary

The project addresses the problem of the timely detection of diseases in tea leaves by implementing the methods of deep learning. It enables the detection and classification procedures to be automated with astounding accuracy by incorporating transfer learning, ensemble modeling, and Error Level AnalysisThe project addresses a complex problem of the early detection of tea leaf diseases by using deep learning methods. Throughout the incorporation of transfer learning, ensemble models and Error Level Analysis, it simplifies the automatization of detection and classification with exceptional accuracy. This technology reduces manual intervention thus crop loss is reduced, sustainable solution to improving tea production and agricultural management.

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Chapter 6

Conclusion

6.1 Summary

In this study, We have demonstrated the efficiency of deep learning models in AD classification based on these MRI images. In this work, We have demonstrated an enhanced model of tea leaf disease recognition by deep Learning methods, particularly EfficientNetB0 and EfficientNetV2B1. We applied this data set in a layer analysis ELA. Subsequently we converted all the images into 224 and it employed the resizing, rescaling, flipping, rotation, contrasting and zooming methods of data augmentation. We are now deep learning in applications.

Deep learning techniques are used now in classification. The data sets used and the resulting steps and model are the reasons behind the high performance of our developed model in tea leaf disease detection. The high performance of our model, in turn, is the reason why we can further enhance the efficiency by applying advanced deep learning architectures such as Transformer on such data sets. Our model helps pathologists and medical professionals with identifying tea leaf diseases.

6.2 Limitation

Notwithstanding its effectiveness, the project is limited in a number of ways. Availability of a large and diverse dataset is also critical in the performance of the deep learning models; inadequate or imbalanced data may decrease accuracy. The difference in environmental conditions which includes lighting, and the orientation of the leaves as well as the background might also influence the outcome of detection. Also, these models are not easy to train and implement, and they are computationally very demanding and thus may be hard in a low-resource or small-scale farmer setting. The machine might not be able to generalize to unknown types of disease or uncommon forms not represented in the training sample. Also, since farmers are not always technically savvy, they may struggle to operate the AI-based solution without a guide and constant maintenance is required to maintain the effectiveness of the system as new diseases develop.

6.3 Future Work

The future work on this project could focus on some essential areas to make it more efficient and user-friendly. To begin with, the dataset can be prepared to encompass an expanded collection of high-quality images, especially those that represent rare and new tea leaf illnesses, and this would improve the generalization and strength of the model. Second, the introduction of real-time detection capabilities via mobile applications or edge devices would allow farmers to identify diseases in the field, and not require more refined computational resources. Thirdly, a more inclusive disease management system could be achieved by integrating deep learning models with other approaches that might include the use of IoT-based environmental monitoring to collect more comprehensive data or drone imagery. Finally, the system should be updated regularly and continuously, which would make it receptive to new trends in the diseases and the changing environmental conditions, thus leading to long-term sustainability and useful application in tea plantations.

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