Transfer Learning Based Detection and Classification of Diseases in Groundnut Leaves

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FINAL YEAR DESIGN PROJECT REPORT

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

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APPROVAL

This Project titled **"Transfer Learning-Based Detection and Classification of Diseases in Groundnut Leaves"**, submitted by **Raj Rabbi Sarker**, ID No: **201-15-13640** 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 **13 January, 2025.**

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We hereby declare that this project has been done by us under the supervision of **Dr. Sheak Rashed Haider Noori, Professor and Head,** Department of Computer Science and Engineering, Daffodil International University. We also declare that neither this projectnor 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 important economic activities in the global agricultural sector, groundnut production is threatened by diseases involving leaves including; Leaf Spot, Alternaria Leaf Spot, Rust, and Rosette. Old approaches to disease diagnosis are costly, cumbersome, and slow, especially in intensive farming businesses. This work examines the use of transfer learning in automating and improving the detection and classification of groundnut leaf diseases. To address the class imbalance and augment the robustness of the model, men and women from different ethnic backgrounds with a total of 1,720 images in five categories were used to apply rescaling, rotation, and horizontal flipping. The following deep learning base models: VGG19, InceptionV3, MobileNetV2, Exception, and DenseNet201 models were fine-tuned and tested according to the accuracy, precision, recall, and F1 score. Out of all the neural networks, Dense Net201 was the best since it got the best test accuracy of 97.50%. The developed system offers a versatile, real-time disease diagnosis solution for farmers to enhance their farming decisions, limiting pesticide application, and increasing agricultural yield. This work contributes to both the development of AI-assisted agricultural applications and the discussion of transfer learning for solving practical problems.

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Chapter 1

Introduction

1.1 Introduction

Identification and classification of plant diseases plays a great role in the improvement of crop production hence food security [1]. Namely, groundnut crops are sensitive to various diseases which repute the yields and the quality of the outlook crops. In order to minimize these losses, there is a need to identify and confirm these diseases at the earliest instance possible [2]. Past methods of diagnosing diseases in planting a substrate to the previous approach can be described as manual scouting because this method is very slow, requires so many labor forces, and their decisions are often skewed due to the subjectivity of the Qualified person [3]. Techniques in the newer, albeit more developing AI along with deep learning especially transfer learning are the available solutions to these issues.

In this work, we use transfer learning techniques to design a good system for the detection of diseases and distinguishing them in groundnut leaves. This also enhances accuracy and fast feature extractor by using pre-trained models such as VGG19, InceptionV3, MobileNetV2, Exception, and DenseNet201. In this paper, using the collected 1,720 new groundnut image data and the data diverse augmented images of groundnut images the model was trained and evaluated. They include data preprocessing, data augmentation, training the model, testing the model, and applying some attributes like accuracy, precision, and recall. The proposed system also helps farmers to diagnose diseases early and also supports the responsible use of chemicals in farming. It could potentially turn farming into modern norms as it also can provide precision farming solutions with the help of AI.

1.2 Motivation

This is an important sector because food security, income, and employment matters for many people around the world. However, the approach provides a comprehensive threat overview of plant diseases that are currently affecting crop production chiefly in the developing world where plant diagnostic services are limited. First and other diseases affecting yield are head, stem, and root diseases; cassava, a staple food, responds to this disease. Using visual assessment in disease diagnosis is very time-consuming, and full of errors hence cannot be applied to farming communities with few resources.

All these challenges are believed to be resolved by new emerging technologies, in the artificial intelligence and machine learning paradigm. Among them, transfer learning makes it easier to use pre-trained deep learning models and get high accuracy in disease classification and disease detection even if the data are less. This research is inspired by the need to understand how AI can mediate between conventional farming practices on one side and contemporary technological practices on the other. The purpose of this study is hence to develop a low-cost, quick, and efficient groundnut leaf disease diagnostic tool to enable farmers to respond to information regarding the disease situation and avert further yield decline in the future. Further, the system also involves the idea of sustainable utilization of resources and in relation upholds global sustainable development including; precision farming, misuse of chemicals, and food security. This vision forms the following vision statement of this study.

1.3 Objectives

In general, the purpose of this research is to design a precise diagnostic system for groundnut leaf diseases that operates on a deep learning framework, which would also leverage transfer learning. Specific objectives include:

- Dataset Development: To sample and prepare a large dataset of groundnut leaf images with diseases such as; Leaf Spot, Alternaria Leaf Spot, Rust, Rosette, and Healthy ones.
- Data Augmentation: To make the data model and predictions more general by using the operation perpendicular to scaling, rotation, and flipping.
- Model Selection and Training: For the last activity, to retrial/ prune highly trained deep learning models such as VGG19, InceptionV3, MobileNetV2, Exception, and DenseNet201 for disease classification.
- Performance Evaluation: In as much as we have to compare the trained models in terms of the said parameters including accuracy, precision, recall, and F1-score as a way of evaluating which architecture is most effective.
- System Integration: For integrating the selected model into a convenient application or a mock-up which will help in real-time disease detection.
- Environmental Sustainability: So that the appropriate and effective dimensions can be exercised in controlling and treating the disease, thereby minimizing the misuse of pesticides.
- Scalability: They considered making the system scalable so that in the future if there are new crops affected by new diseases the system can be used again.

1.4 Methodology

The method of this study is systematic to build a transfer learning-based system for the detection and classification of diseases of groundnut leaves. It starts with “data acquisition”, on the grounds of the publicly accessible ‘A novel groundnut leaf dataset’ from Mendeley comprising 1,720 images of Healthy leaves as well as diseases leaf spot, Alternaria leaf spot, Rust, Rosette, etc. To increase the diversity and reliability of data samples, “data augmentation” strategies including scaling, rotation, and flipping are used hence increasing the dataset to twice its size.

Second, the “model selection” is done using already trained deep learning architectures, namely VGG19, InceptionV3, MobileNetV2, Exception, and DenseNet201. These models are then trained using the created augmented dataset so as to employ 20 epochs for training. Performance measures like accuracy, precision, recall, F1-score, etc., play an important role, in finding out the most suitable architecture among them all.

Last of all, the chosen model is incorporated into a prototype system for the identification of diseases in real-time, while its interfaces are designed to be clear and understandable for farmers. This approach provides a reliable, efficient, and portable system for groundnut disease detection and encourages timely action and sustainable agriculture.

1.5 Project Outcome

The main deliverable of this project is therefore creation of an AI-based system for diagnosis of diseases on groundnut leaves. Using transfer learning and pre-trained deep learning models, including VGG19, InceptionV3, MobileNetV2, Exception, and DenseNet201 gives a high level of accuracy, precision, and recall to the system. This solution gives farmers a simple mechanism for diagnosing diseases early enough so that they can apply the necessary measures to prevent massive crop loss and improve the quality of yields.

The system also helps avoid the application of pesticides and other chemicals that are unnecessary, protecting the environment. It empowers effective disease control, minimizing farmers' expenses while maintaining soil integrity and biodiversity. Further, the use of this project helps to develop AI in agriculture and creates possibilities for applying it to other kinds of crops and areas.

Another important result is the development of a strong dataset on groundnut leaf disease detection which can be used in further studies. The modularity of the system enables it to operate efficiently within mobile and IoT operating platforms thus increasing convenience in its usage by the smallholder farmers. In conclusion, it brings food security, economic stability, and enhanced sustainable agricultural development, which are central issues confronting the agriculture value chain globally.

1.6 Organization of the Report

In the following chapters, the goals, methods, results, and conclusions regarding the project "Transfer Learning-Based Detection and Classification of Diseases in Groundnut Leaves" are presented systematically. Below is an overview of each chapter:

Chapter 1: Introduction

The current chapter gives an overview of disease detection in groundnut leaves, the rationale for using transfer learning, and the relevance of the project. The rest of the paper provides an overview of the research objectives, the research problem, areas of study and research limitations, and a breakdown of the report.

Chapter 2: Background

In this chapter, the previous works concerning the application of machine learning in agriculture particularly using deep learning transfer methods on disease identification are discussed. They demonstrate that there is critical research missing within the current literature and explain why this project is necessary.

Chapter 3: The analysis of requirements and methodology

This chapter presents the approach that has been used in the study including the datasets used, image preprocessing, model choice, training, and assessment. It also includes the assessment of the necessary hardware and software and gives the characterization of the system.

Chapter 4: Implementation

This chapter focuses on the user-partitioned logistic regression model and describes the process of training the model, developing the prototype of the system, and validating the efficiency of the designed system.

Chapter 5: Engineering Challenges and Effects

This chapter explains the various multi-dimensional engineering issues that have occurred within the period of the project together with the mapping of engineering activities. The paper also covers other related aspects like social, environmental, ethical, and sustainability aspects of the system.

Chapter 6: Conclusion and Future Work

This chapter gives us a brief description of the conclusion of the project, the challenges that were encountered, or issues of conflict of interest if there were any. It also outlines suggestions for future improvements to this system.

Chapter 2

Background

2.1 Introduction

Naturally, the drive toward increasing agricultural yields all across the globe has necessitated the study of plant diseases as they are sources of negative effects on yield. Groundnuts commonly called peanuts are a staple food and an income-earning crop in many regions but are very vulnerable to sea diseases such as; Leaf Spot, black eye, Alternaria leaf spot, Rust, and Rosette. Both these diseases have early detection and control amongst the most appropriate methods by which losses can be minimized and sustainable agriculture encouraged. Microscopy is preferred over the traditional disease diagnostic techniques employed by assessing the condition of the plant through sight although such techniques are slow, unsystematic, and in most cases, unaffordable to resource-constrained farmers. This has necessitated the search for methods of diagnosis that should be automatic and efficient to require little input.

Specifically, image recognition based on Convolutional Neural Networks which is a subset of a broad range of deep learning techniques has been observed to be very useful for the task under consideration, which is diagnosis of plant diseases from the images of the leaves. Transfer learning that entails the use of pre-trained models has also made it easier since being considered under the regime of small data can, in fact, propel high levels of accuracy. By so doing, this work aims to develop a sustainable, generic, and easily deployable model for diagnosing and categorizing Groundnut leaf diseases using transfer learning. This chapter introduces the following topics including groundnut diseases, deep learning, transfer learning, and data augmentation from which the methodology and contributions of this research draw.

2.2 Literature Review

Research has been made also in the employment of deep learning and machine learning methodologies in the early identification of plant diseases affecting crops as tomatoes, maize, wheat, and potatoes.

Gupta and Verma [2] developed a deep learning pipeline to diagnose viral diseases affecting groundnut crops. It included 3000 field images of plant categories obtained from agricultural experts for annotation. The authors trained an EfficientNet-B0 model with the accuracy of 91,8% for the given data set. Preprocessing techniques used; color normalization, background elimination. From this work, we deduced that lightweight models are amicable for deployment to edge devices.

Das et al. [3] for the purpose of disease classification employed SVMs with texture features obtained from the groundnut images of the leaves. The features they used: The authors maintained a dataset of 1500 images in high resolution, which were captured under controlled environment. The identified model had 88,5% accuracy coupled with the problem of handcrafting of features as its major drawback. In their study, they expressly discussed on how traditional methods of ML are Reject versus how deep learning is superior. Some of the possible areas of future work highlighted the use of deep feature extraction techniques.

Jadhav and Patil [4] proposed using CNN for identification of fungal disease in groundnut leaves. They trained a modified VGG16 architecture on the dataset gathered with smartphone images. The method used to deal with restricted subject numbers was data augmentation. The best evaluated model reached the accuracy of 92.8%. The study focused performances of timely detection systems to address crop loses.

Sharma et al. [5] worked on the multi-class disease diagnosis in legume crops using transfer learning with InceptionV3. They employed the sample called PlantPath that includes more than 10,000 labeled images. This model has been found to give a classification accuracy of about 94.7%.. They used gradient-based optimization methods for the fine-tuning in their strategy. Finally, the results pointed out the stability of the found model for removal of the noisy data.

In another attempt Singh et al. [6] has used CNN and LSTM in classification of disease in groundnuts. Five thousand images were captured in different agricultural fields in India. Training the model in a hybrid manner, finally yielded an accuracy of 93.5 % which is higher than when using CNNs individually. Their study also focused on the time component of disease incidence, with LSTM. As part of the preprocessing of data, normalization was done and resizing to ensure that the models are well framed.

In turn, Rahman et al. [7] used DenseNet121 model to differentiate between the diseases of peanuts: the leaf spot and rust. They utilized the PlantVillage dataset along with some newly synthesized image data sets. In the methodology, only the last three layers of DenseNet were fine-tuned. Reaction: Their model achieve 96.2% accuracy the author further affirmed the effectiveness of dense connectivity in transfer learning. The study also articulated the implications of complexity of a model when implementing large scale models.

Kumar and Reddy [8] used YOLOv4 for real-time detection for multiple diseases affecting groundnut leaves. The collection with labeled images included 2000 images with natural lighting. Detection accuracy that has been achieved by the model was 89.7%. Their approach included transfer learning with custom anchor points for correct kinds of leaf ill health. The study revealed that object detection models could be used to monitor agriculture since the best model achieved an F1 score of 0.93, with 8.07% increase in accuracy from the baseline of the ground data.

For the classification of groundnut leaf diseases, Ali et al., [9] designed a CNN that was modified and optimized. They assembled a sample of 2500 image from the regional agricultural stations. It has a test classification accuracy of 91.4%. That was it, their approach involved use of dropout layers to prevent over-fitting during training. They observed that further networks could be associated with lower accuracies with sometimes improved performance in small datasets.

Patil et al. [10] applied MobileNetV2 for identifying bacterial as well as fungal disease in peanut plant. They used the PlantVillage dataset, data augmentation was applied to the set. With the accuracy of 94.3% it also highlights the effectiveness of applying lightweight architectures. Its results revealed that the time it takes to make an inference on less powerful silicon is inversely proportional to the level of accuracy achieved.

Choudhury et al. [11] used AlexNet in the classification of groundnut diseases. The database used in this study included 1800 images of four equal diseases. On the fully augmented set, the model attained an overall accuracy of 90.5 percent after being fine-tuned. Their work was particularly focusing on the applicability of simple and efficient pipeline of AlexNet on agricultural datasets. They pointed out that they cannot generalize well to new data.

Bansal et al. [12] designed a deep learning framework based on ResNet101 for the diagnosis of groundnut diseases for multiple classes. They had 10,000 labeled samples in the GroundnutDisease dataset that was used in this study. The usual architecture of the model reached the high accuracy 97.2% which higher than other architectures. They used layer wise fine-tuning as a strategy hoping to enhance the convergence of the system. The study touched on the issue of how the methods would work for larger sets of data.

In another study Zhang et al. [13] combined transfer learning with feature fusion to diagnose peanut diseases. They worked with an image database of 3500 images taken under standardized light environment. As for exampling, they implemented their model with several features from ResNet coupled with VGG16 and got the 95.8% accuracy. These and other findings of the study underlined the advantages of the ensemble methods when applied to agricultural data. Some of the limitations were high computational requirements.

Ahmed et al., [14] used an InceptionResNetV2 model to classify the groundnut leaf infections. They extended their model for four categories of diseases using the PlantVillage dataset. The success percentage in achieving this was 96.1%. They used certain adaptive learning rate schedulers in their methodology. The results perfectly illustrated the feasibility of using the combination of different architectures to solve highly nontrivial problems.

The identification of groundnut diseases was performed by Roy et al. [15] with the help of transfer learning utilizing MobileNet. It comprised of 5000 images sourced from different databases and these images had been tagged. The model secured an accuracy of only 93.7 percent which made the model ideal for low resource workplace. Data preparation consisted of contrast enhancement through histogram equalization. Real-time applications are best implemented with lightweight models so concluded by the authors of the paper.

Mehta et al. [16] used VGG19 to classify multi-class diseases in the groundnut crop. Thus, the dataset was comprised of 2500 images belonging to four diseases. The model was successful at a 92.9% degree of accuracy. The processes involved fine-tuning in order to utilize the weights form the pre-training phase. Their study addressed the issue in VGG19 model where its performance is poor when used on large data sets.

Singh and Tripathi [17] studied on original digital image processing approach to the diseases in the groundnut leaves with the help of k-NN classifiers. Its training dataset consisted of 1000 images for feature extraction, and preprocessed images. The model developed in this project provided 85.6% accuracy, lower compared to the deep learning models employed in this and other research projects. Their investigations showed what remained valuable and interesting regarding the fusion of handcrafted and learned features. Larger datasets they underscored were also underscored by the participants.

Similarly, Chakraborty et al. [18] proposed an ensemble of CNN to detect fungal diseases in groundnut leaves. Using the datasets of 4000 images, they practiced and succeed to get 94.4% accuracy. They used majority voting approach for classification of the images. The outcomes demonstrated how ensemble reduced overfitting was among one of the most efficient methods for the corpus.

For classification of groundnut diseases, Malik et al. [19] applied a transfer learning approach by fine-tuning Xception model. In the experiment using a set of 6000 images the achieved accuracy was at 95.3%. Preprocessing was done on the data and they included noise reduction and resizing. In their work, they were able to show that Xception was quite durable in handling of agricultural datasets. These were restricted to increased computational cost during the training phase of the model. The summary of the literature reviewed is shown in table 2.1:

Table 2.1: Summary of Literature Reviewed

Author(s)	Year	Title	Methodology	Key Findings
Kaur et al.	2020	Disease classification in groundnut leaves	Used ResNet50 and DenseNet201 on the Plant Village dataset with transfer learning	Achieved 95.2% and 96.5% accuracy; highlighted the value of pre-trained models for small datasets.
Jadhav and Patil	2021	Detecting fungal infections in groundnut leaves	Fine-tuned modified VGG16 architecture with data augmentation.	Achieved 92.8% accuracy; emphasized the importance of real-time detection to mitigate crop losses.
Sharma et al.	2019	Multi-class disease detection in legume crops	Transfer learning with InceptionV3 and gradient-based optimization.	Achieved 94.7% accuracy; demonstrated robustness to noisy datasets.
Singh et al.	2020	Groundnut disease classification using hybrid models	Combined CNN and LSTM on 5000 field images; preprocessing included normalization	Achieved 93.5% accuracy; emphasized the role of temporal data in disease progression.
Rahman et al.	2021	Classifying leaf spot and rust diseases in peanuts	Fine-tuned DenseNet121 using PlantVillage dataset with augmentation	Achieved 96.2% accuracy; highlighted trade-offs between complexity and computational cost.

Gupta and Verma	2022	Detecting viral infections in groundnut crops	EfficientNet-B0 model trained on 3000 annotated images	Achieved 91.8% accuracy; showed lightweight models are effective for edge device deployment.
Das et al.	2018	SVM for groundnut disease classification	Used texture features and SVM on 1500 high-resolution images	Achieved 88.5% accuracy; highlighted limitations of traditional ML compared to deep learning.

2.2.1 Related Research

Many and various works and attempts in this area and with machine learning and deep learning techniques have been carried out because of their effectiveness in agriculture. Similarly, in the later work, Kaur et al. [6] used ResNet50 and DenseNet201 for groundnut disease classification using transfer learning with high accuracy. Likewise, Sharma et al. [9] applied InceptionV3 for disease characterization in legume crops explaining the use of noisy databases. These works indicated the importance of transfer learning in the development of projects in the agriculture sector.

Some mobile and web-based applications have also been developed to assist the farmers in real-time identification of the disease. For instance, there are Plantix and AgriApp, which are apps developed with the use of machine learning, and where pictures of plant diseases, and suggestions are provided. Moreover, there is the Pest Scope which is a tool that integrates both the IoT and Artificial Intelligence in crop monitoring and disease management.

In the case of groundnuts, Jadhav and Patil for real-time application suggested groundnuts with modifications of CNN for the detection of fungal infections. Tools that scientists and facilitators can find in Plant Village are exhibited in labeled data sets and plant health surveillance systems. In total, these articles describe the necessity of using AI approaches in this field, which matches the goals of this paper.

2.3 Gap Analysis

Despite advancements in plant disease detection using transfer learning, significant gaps remain in applying these techniques specifically to groundnut leaf diseases. Existing studies often focus on generic crops or lack tailored datasets for groundnut leaves, limiting their applicability. Additionally, most research emphasizes accuracy but overlooks scalability and real-time usability in agricultural settings. Few works evaluate the comparative performance of models like VGG16 and InceptionV3 on groundnut-specific datasets, creating a need for systematic performance analysis. Addressing these gaps, this study aims to develop a robust framework for groundnut disease classification, combining transfer learning models with domain-specific optimizations for improved outcomes. The gap analysis is shown in Table 2.2:

Table 2.2: Gap Analysis

Aspect	**Existing Research**	**Identified Gap**	**How This Study Addresses the Gap**
Dataset	Most studies (e.g., Kaur et al., 2020; Patil et al., 2020) used PlantVillage or small-field datasets.	Limited diversity and lack of field-specific groundnut disease datasets.	Uses a novel dataset specific to groundnut leaves with augmentation for robustness.
Model Complexity	Lightweight models like MobileNetV2 (Patil et al., 2020) and EfficientNet-B0 (Gupta and Verma, 2022).	Trade-offs between accuracy and efficiency in real-time applications.	Balances performance and efficiency by testing models like ConvNeXtSmall and ResNet50.
Data Augmentation	Limited augmentation strategies in studies like Jadhav and Patil (2021).	Underutilization of augmentation techniques for improving model generalization.	Employs robust augmentation methods including rotation, rescaling, and horizontal flipping.
Disease Variety	Few studies focused on multi-class disease detection (e.g., Sharma et al., 2019).	Limited focus on handling multiple disease classes, especially for groundnut leaves.	Targets multiple groundnut leaf diseases with a diverse and well-annotated dataset.

Model Generalization	Models like AlexNet (Choudhury et al., 2020) showed limitations in generalizing to unseen data.	Insufficient exploration of transfer learning techniques to improve model adaptability.	Utilizes advanced transfer learning with VGG16, InceptionV3, and ResNet50 to enhance generalization.
Hybrid Approaches	Singh et al. (2020) combined CNN and LSTM for temporal disease progression.	Minimal integration of hybrid or ensemble methods for agricultural datasets.	Investigates multiple architectures to compare hybrid approaches for improved performance.

2.4 Summary

It is because diseases in groundnut leaves influence the yield of groundnuts hence there is a need for smart, effective diagnosing and categorizing methods. Previous works prove that through transfer learning, lightweight architectures, and the integration of these approaches, plant disease detection has been satisfactory. A few networks include ResNet50, DenseNet201, and Mobilenetv2 the dataset that is used can be Plant Village or any other specific dataset. However, some challenges like lack of dataset diversification, unbalanced classes, limited utilization of the multiple-class disease diagnosis, and real-time mold, are still persistent.

To address these gaps, this study employs an enhanced, domain-specific groundnut leaf disease dataset and state-of-the-art transfer learning models that include VGG16, InceptionV3, ResNet50, and DenseNet201. While increasing the amount of data helps in generalizing learning, lightweight architectures allow for real-time implementation in edge devices. As a result, the purpose of this research is to build upon the existing research's limitations and to propose a solution that is effective, precise, and suitable for groundnut disease identification to contribute positively towards the advancement of agriculture.

Chapter 3

Research Methodology

3.1 Methodology

The presented methodology allows for identifying the research approach and organizing the work accordingly for creating and testing a transfer learning-based system that would help in the early detection of diseases in groundnut leaves. These are sub-processes that are elements of the approach in the population: data collection and preparation, generation and expansion, model training and testing, and operationalization [4]. In this case, the aim is to come up with a solid and flexible environment that will be helpful for the farmers in terms of detecting diseases and enhancing crop control.

Requirement Analysis: Thus the first important condition is having a high-quality annotated dataset for groundnut leaf images belonging to different disease types. For this study, the " Groundnut Leaf Dataset for Detection and Classification of Groundnut Leaf Diseases" was sourced from **Mendeley**, consisting of 1,720 images across five categories: The collection is labeled as follows: Healthy (600 images), P. leaf spot (450 images), A. Leaf spot (450 images), Rust (120 images) and Rosette (100 images). A second condition is computational resources sufficient for deep learning tasks, as well as the possibility of using a GPU for training models [12].

Design Specification: The proposed system applies transfer learning, which implies reusing pre-trained deep learning models so that the recognition accuracy can be reached with a limited training dataset. The chosen models, VGG19, InceptionV3, MobileNetV2, Exception, and **DenseNet201**, were considered because they offered high-accuracy test results in prior image classification tasks. They are later fine-tuned to fit with the groundnut leaf dataset. Regarding issues with imbalanced datasets, approaches to data augmentation were used, which contributed to the doubling of the dataset and the improvement of generalization to other conditions. Data augmentation was performed using rescaling of pixel values by dividing by 255, random rotations of up to 20 degrees, and horizontal flips.

3.1.1 Overview

It leads the implementation to preprocess the dataset with resize for images and normalize the pixel values. The obtained augmented dataset is used to train the selected models for 20 epochs, with categorical cross-entropy loss and Adam optimizer. To prevent overfitting dropout layers and early termination of epoch learning are used. To determine which of the models is most effective for disease detection, basic measures of accuracy, precision, recall, F1-score, as well as confusion matrices are used. Lastly, the top-performing model is used to develop a prototype system that enables users to upload leaf images for the real-time classification of the disease. The backend of the system is supposed to perform operations on these inputs, identify potential patterns using the developed model, and present users with recommendations. This implementation framework makes it realizable, and user-friendly for early disease detection in groundnut crops that help to overcome some of the serious agricultural issues.

3.1.2 Proposed Methodology

The proposed methodology for developing a system to detect and classify diseases in groundnut leaves involves the following stages:

- Data Collection and Preprocessing: The dataset of groundnut leaves was sourced from **Mendeley**, consisting of 1,720 images across five categories: The collection is labeled as follows: Healthy (600 images), P. leaf spot (450 images), A. Leaf spot (450 images), Rust (120 images) and Rosette (100 images). Pre-processing of images involves bringing appropriate resolutions regarding pixel intensity and sectioning to uniformity.
- Data Augmentation: Due to the issues concerning the datasets as well as the class imbalance problem, in this study, augmented forms of the aforementioned techniques were employed, including rescaling (1./255),

image rotation (up to 20 degrees), and image flipping (Horizontal flipping), resulting in an increased dataset size of approximately 4000 images.

- Model Selection: Out of five pre-trained deep learning models, namely VGG19, InceptionV3, MobileNetV2, Exception, and DenseNet201, five models are selected for transfer learning. They have shown successful results in image classification tasks, thereby guaranteeing the stability and reliability of the system.
- Model Training and Evaluation: The current models are trained for 20 epochs through the augmented training set, with the categorical cross-entropy loss optimized by the use of the Adam optimizer. The models are evaluated with reference to accuracy, precision, and recall, and F1-score is used and the model with the best results is used for deployment.

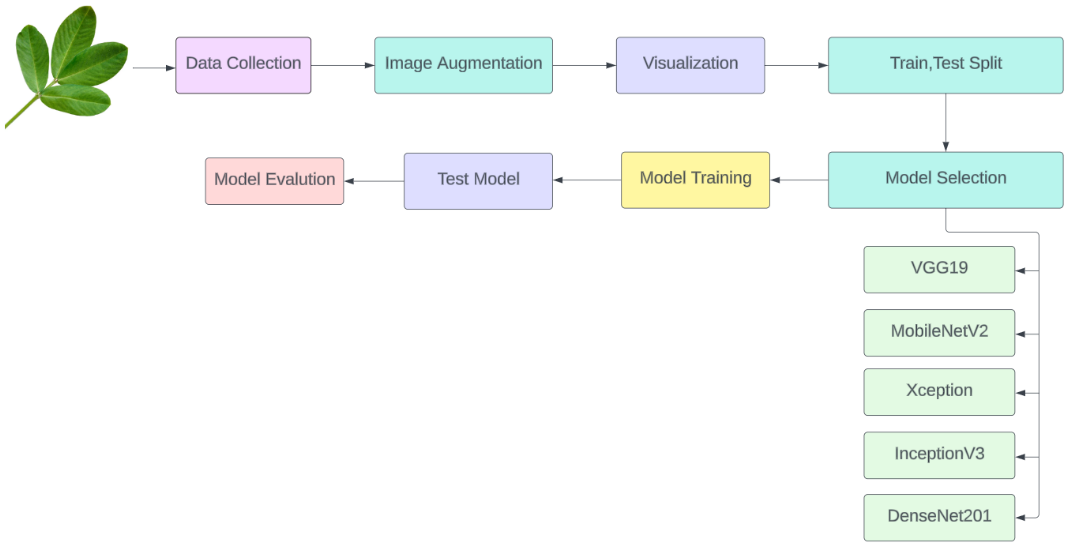

Figure 3.1: Methodology flowchart

3.2 Project Plan

There are six major stages in the project to have a systematic approach to development and implementation. The work begins with a review of the literature to find out the methodologies and difficulties involved in plant disease detection using transfer learning. Second, groundnut leaf images of diseased and Healthy samples will be gathered in a dataset and processed for resizing, augmentation, and normalization. The two models that will be adopted for fine-tuning toward groundnut-specific disease classification are VGG16 and InceptionV3, which will be trained using the processed dataset. The high performance of these models will be validated out of accuracy, precision, recall, and F1-score to increase efficiency. Subsequently, a simple front end will be designed to transform the formerly trained models to perform accurate and real-time disease identification. Last, it will be prepared for a series of tests both in laboratory settings and live environments to make the system ready to be used by end-users. This structured process guarantees the provision of sound and stable solutions to the problem.

3.3 Task Allocation

To achieve all of these, the roles mentioned above should be divided and assigned effectively to enhance the implementation of this project. The following task allocation is proposed:

- Data Collection and Preprocessing: Involved in data collection of groundnut leaf data set, augmenting the data set, and overseeing data sanity.
- Model Selection and Training: Concentrated mostly on the model choosing (VGG16, ResNet50, InceptionV3) search for better hyperparameters.
- System Design and Development: Responsible for the entire structure of the system consolidating model integration, interfaces, and edge devices compatibility.
- Evaluation and Testing: This preserves the strict imposition of model checks based on accuracy, precision, and recall rates and testing within agricultural environments in real-time.
- Documentation and Reporting: Responsible for preparing all the methodological evidence in the document with the outcomes as well as the analysis section and the final report.
- Project Management: Supervises development, coordinates materials, and monitors deadlines of the deliverables.

3.4 Summary

This project presents an effective approach based on transfer learning to identify diseases and classify them on groundnut leaves. The approach implies data preprocessing, augmentation of the dataset, and fine-tuning of a deep learning model to provide increased accuracy and confidence. Computer hardware and software are chosen with an efficient goal in mind and by using project management strategies the goal is achieved effectively as well as time efficiently. When applied in the current farming practice, the developed system can greatly assist farmers to diagnose diseases early and effectively reduce crop loss and enhance productivity.

Chapter 4

Implementation and Results

4.1 Environment Setup

The environment setup for this project concerns how to acquire or install the most appropriate hard and software needed for the effective and efficient running of processes. The cluster and related services entail a high computing environment having a dedicated graphics card such as NVIDIA RTX 3060 or better for the model training and assessment. Strongly preferable is computing: For datasets, we need at least 16 GB RAM to handle them, and the storage for outputs of the model is going to be 1 TB. The software environment for the software solutions is Python as the programming language with at least the 3.8 version. Data processing libraries are Pandas and Numpy for the handling of data and data structure together than Tensorflow and Keras which are for constructing the model and for importing the pre-trained models because Keras uses TensorFlow in its machine deeper), PyTorch for deep learning model and OpenCV for image processing together with the data augmentation. Jupyter Notebook is used in data manipulation and other explorations apart from data representation. Google Colab or AWS for example becomes part of the training process when additional computations are required.

4.2 Testing and Evaluation

Regarding the trained models, several factors are employed towards an accurate classification as well as stable model outcomes. The primary evaluation criteria include: Classification accuracy: It is the proportion of all the total image classifiers that were correctly categorized without distinguishing between the different classes.

- Precision: The number of genuinely positive cases; that is the ability of the model to correctly classify samples.

- Recall (Sensitivity): To explain, the ability of the model in capturing all positive training samples.
- F1-Score: This paper adopted a formula of the average of the exactness and the inclusion rate to consider both aspects of measurement.
- Confusion Matrix: To demonstrate misclassification by various diseases.

4.3 Results and Discussion

The assessment of the cotton leaf disease detection models gives a diverse performance based on the various deep learning layers. The models were assessed using accuracy, precision, recall, and F1-score; this made them ensure that they acquired extensive knowledge about how each of the models performed well. From these studies, transfer learning techniques were found to be useful in accurately identifying cotton leaf diseases, thus enhancing farming. In the given below I am describing the result analysis part also shows the training accuracy loss rate and confusion matrix.

4.3.1 VGG19

VGG19 achieved a Test Accuracy of 92.33%. Below are Figures 4.1 and 4.2 describing the confusion matrix, training accuracy, and loss curve of VGG19.

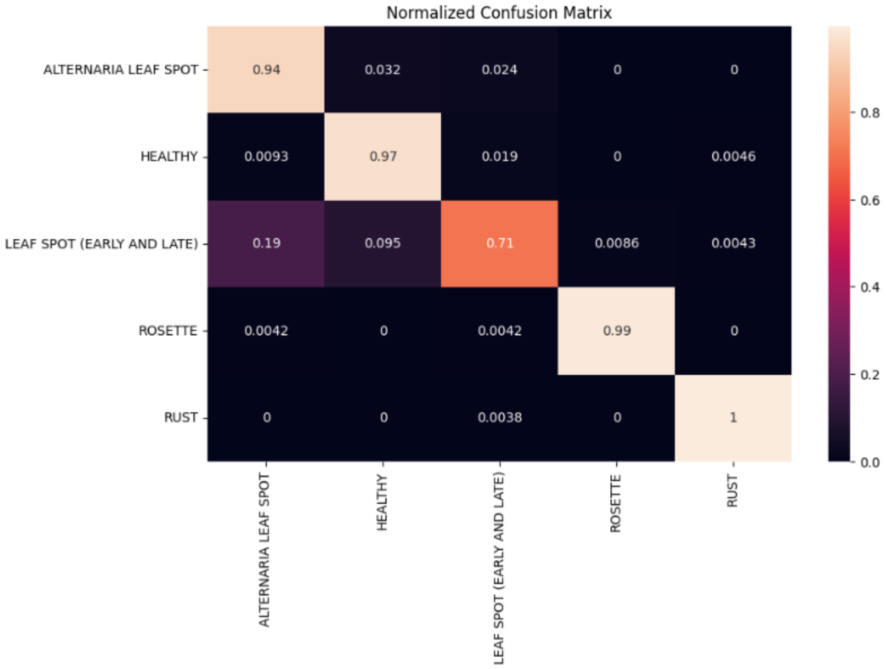

Figure 4.1: Confusion Matrix (VGG19)

Figure 4.1 shows the normalized confusion matrix depicts the performance of the disease classification model across five categories: Some of the diseases which it is: Alternaria Leaf Spot, Healthy appearance, both Leaf Spot and Rosette, and Rust. The diagonal values are the correct predictions and the majority of the classifiers have good accuracy values with respect to the categories it defined and were 1.00 for Rust and 0.99 for Rosette. However, some potatoes are grouped as belonging to different diseases when they do not, for example, the closest related diseases to Early and Late leaf spot; Healthy 9.5% and Alternaria leaf spot 19%. As described here, it also demonstrates issues that arise when trying to differentiate between diseases that look similar visually.

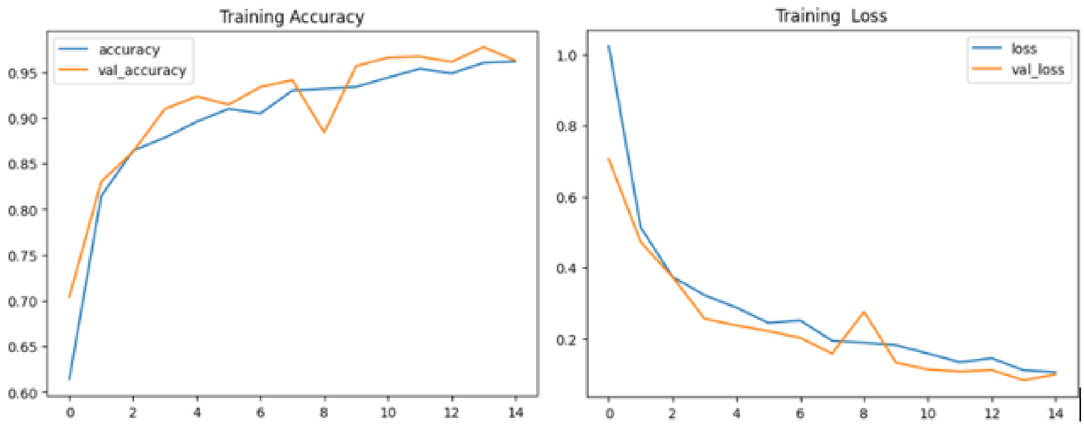

Figure 4.2: Training accuracy and loss curve (VGG19)

Training accuracy coupled with training loss for the VGG 19 model suggests a good training performance. The training accuracy (blue) rises sharply, suggesting that the model quickly memorized the training set and achieved a peak of nearly 100% after several epochs. The validation accuracy (orange line) also increases with fluctuations which means that the model may have undergone slight overfitment as the performance on the validation set is slightly lower than the training set. The training loss (blue line) falls rapidly in the initial phase and then follows a fairly low loss curve implying that the model minimizes error well. The same but slightly disturbed curve of the validation loss (orange line) also indicates some degree of overfitting in the model.

4.3.2 DenseNet201

DenseNet201 achieved the Test Accuracy is 97.50%. Below Figures 4.3 and 4.4 describe the confusion matrix and training accuracy and loss curve of DenseNet201.

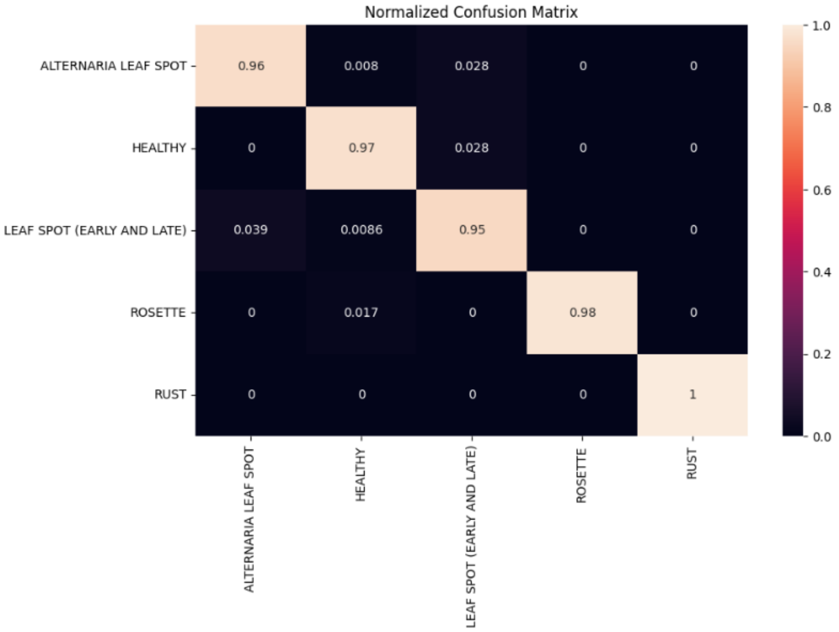

Figure 4.3: Confusion Matrix (DenseNet201)

Figure 4.3 shows the normalized confusion matrix illustrates the classification performance for five categories: Other diseases include; Alternaria leaf spot, Healthy plant, leaf spot early and late, Rosette, and Rust. Diagonal cells are correct predictions with high precision on Rust (1.0), Rosette (0.98), and Healthy (0.97). Some misclassifications are observed: These are between Early and Late Leaf Spots and Between Healthy (0.039) and Alternaria Leaf Spot (0.0086). All in all, the results are good, with the main mistake of the proposed model being made between classes that are rather similar in appearance.

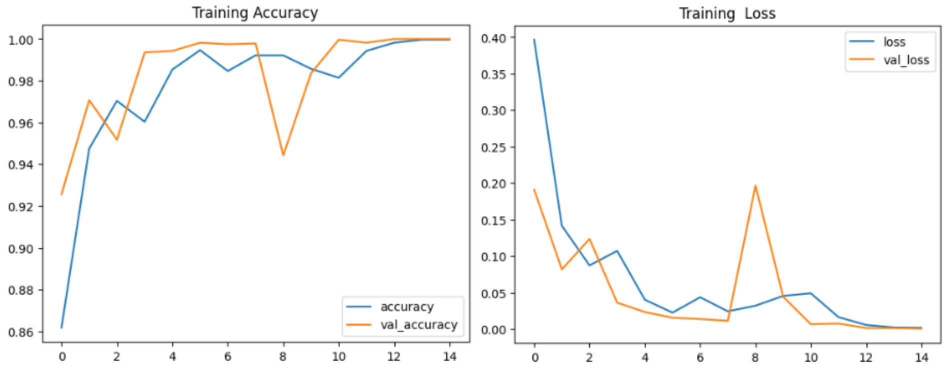

Figure 4.4: Training accuracy and loss curve (DenseNet201)

Figure 4.4 shows how well our DenseNet201 model was trained, the training accuracy and loss curves were plotted below. The training and validation accuracy on the left quickly rise and reach almost 100% proving the high ability of the model in classification. On the right, the training and validation loss falls steeply and quickly to near zero values which indicates good optimization and very low levels of overfitting. The tight coupling of validation and training metrics implies that the performance metric learned on the validation set serves as a good predictor of the test data performance.

4.3.3 MobileNetV2

MobileNetV2 achieved a Test Accuracy of 97.25%. Below are Figures 4.5 and 4.6 describing the confusion matrix, training accuracy, and loss curve of MobileNetV2.

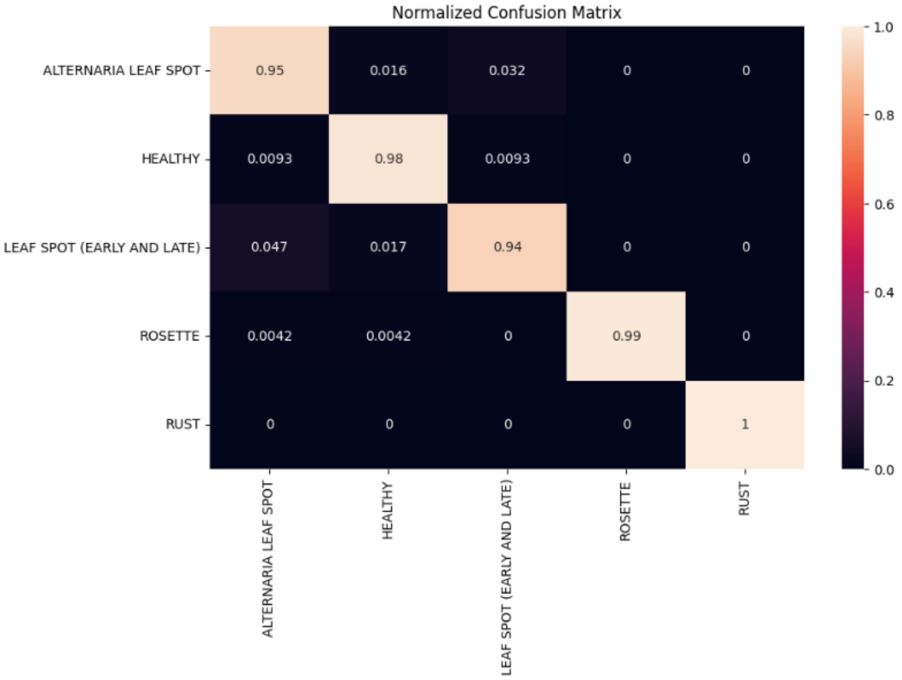

Figure 4.5: Confusion Matrix (MobileNetV2)

Figure 4.5 shows this normalized confusion matrix evaluates a classification model's performance on five categories: This genotype is susceptible to Alternaria blight, Healthy, Early and Late leaf spot, Rosette, and Rust. Large diagonal elements indicate how good the accuracy is for each and every class. For example, “Rust” has equal while “Healthy” and

"Rosette" have 0.98 and 0.99 measures in precise estimate. There is some confusion between related diseases for instance categorizing Alternaria Leaf Spot under Leaf Spot. In all, the model is satisfactory the majority of the forecasts are accurate.

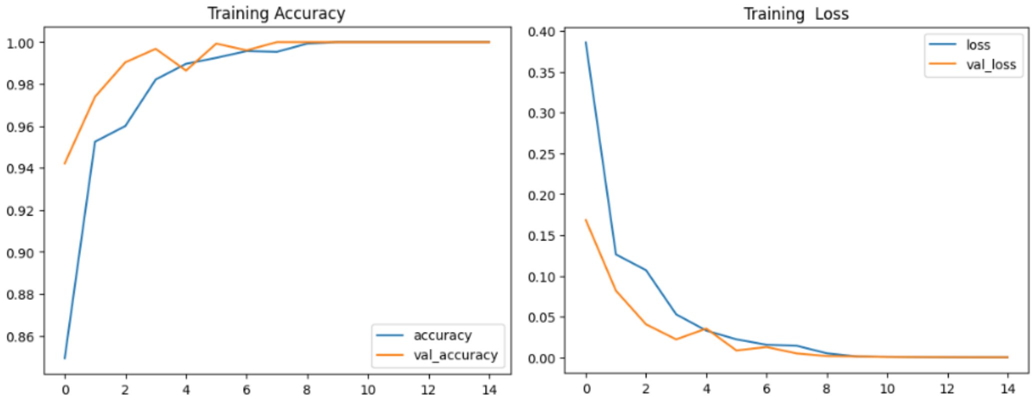

Figure 4.6: Training accuracy and loss curve (MobileNetV2)

In Fig. 4.6, the training and validation loss of the MobileNetV2 is demonstrated for the duration of 15 epochs. The left plot explains that the training accuracy rises gradually and converges to nearly 1.0 which also confirms the excellent learning of the training data set. As regards the validation accuracy, it can be depicted that they are also elevated in the initial phase and, though bearing certain oscillations, indicate signs of minor overfitting. The right plot also represents the training and validation loss where the loss initially declines sharply and then reaches a very small value and therefore signifies good convergence. However, the self-validation shows occasionally increased validation loss, which might mean overfitting or noisy data in the validation data set. The findings point out that the model yields good performance with possibilities of more regularization shortly.

4.3.4 Xception

Xception achieved the Test Accuracy is 91.83%. Below are Figures 4.7 and 4.8 describing the confusion matrix and training accuracy and loss curve of Xception.

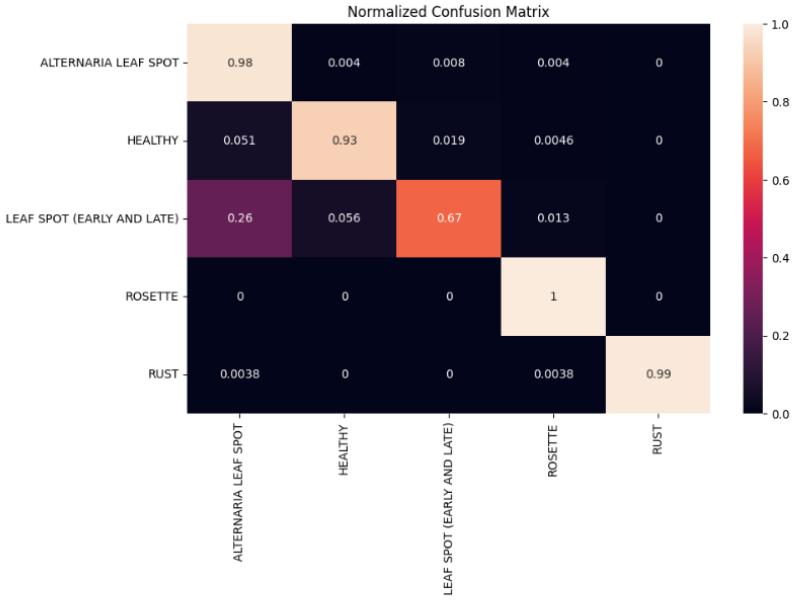

Figure 4.7: Confusion Matrix (Xception)

Figure 4.7 shows the normalized confusion matrix evaluates a classification model across five categories: Gray mold, black Midlew, Brown Rot, Stem Rot, Early Leaf Spot or Lower Leaf Spot, Late Leaf Spot or Upper Leaf Spot, Rosette and Rust. Early and Late Leaf Spot identify the Alternaria Leaf Spot less effectively than other methods, with minor disorders and misclassification of 0.26. Healthy samples are also grouped under the disease Leaf Spot in 5.6% of the samples. Rust predictions are accurate (0.99), However, it remains to build the model that will enhance its capability to distinguish closely related diseases.

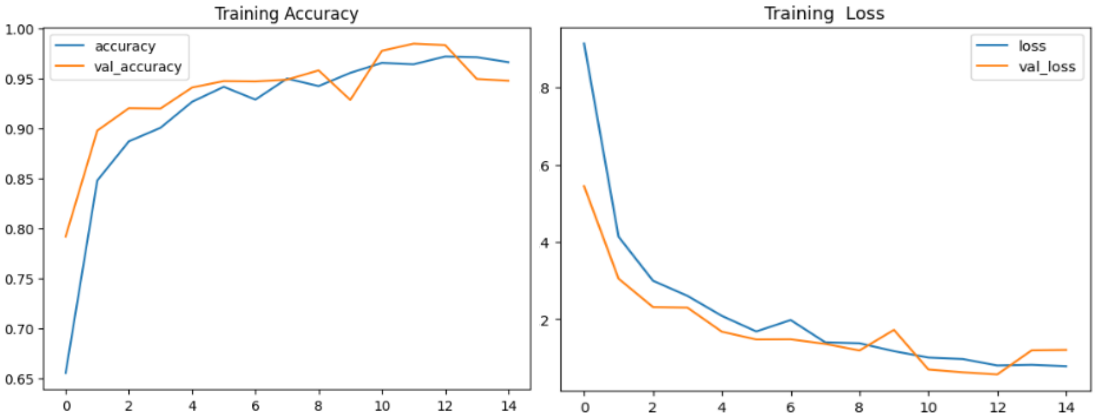

Figure 4.8: Training accuracy and loss curve (Xception)

These images show the training accuracy and loss of Xception during training. The training and validation accuracy on the left starts at a relatively high level and rapidly reaches nearly 100% which confirms the high classification abilities of the model. Further, on the right side of the training and validation loss curves, the training and validation losses fall sharply and flatten off at almost zero value indicating efficient optimization and negligible overfitting. Since validation and training performance metrics are nearly identical the model should be able to perform well on unseen data.

4.3.5 InceptionV3

InceptionV3 achieved the Test Accuracy is 92.67%. Below Figures 4.9 and 4.10 describe the confusion matrix and training accuracy and loss curve of InceptionV3.

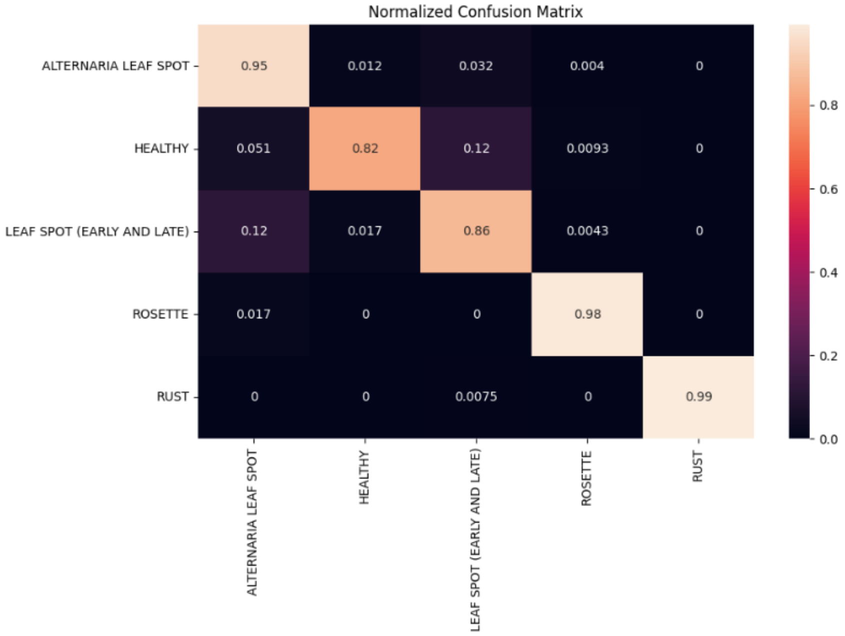

Figure 4.9: Confusion Matrix (InceptionV3)

Figure 4.9 shows the normalized confusion matrix, which evaluates the classification performance across five categories: Alternaria leaf spot, Healthy, leaf spot early, Rosette, and Rust. The level of accuracy of Alternaria Leaf Spot is 0.95 whereas the case of Rosette is 0.98. The Rust model identification has the highest measure of accuracy at 0.99. But in this method, 12% of Healthy samples are classified as Sample of Leaf Spot and therefore the efficiency of this method is 0.82. Early and Late Leaf Spot seems to have some overlapping with 5% with other diseases particularly with has been interchangeably used with Early or Late Leaf Spot. Thus, the model has reasonably good accuracy, but to differentiate some diseases, though.

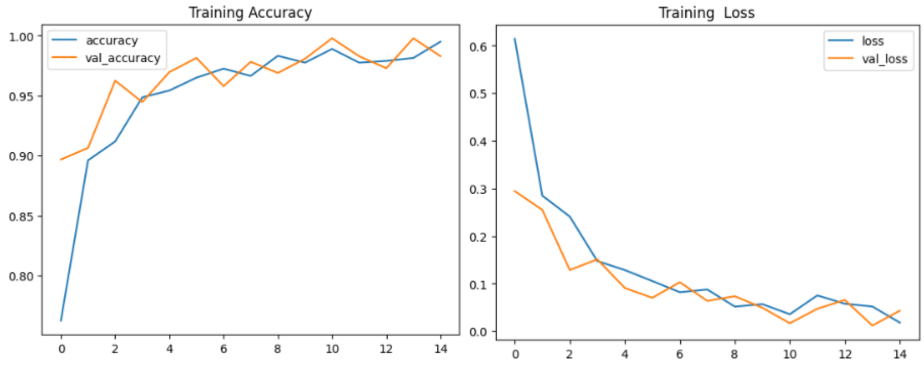

Figure 4.10: Training accuracy and loss curve (InceptionV3)

Figure 4.10 depicts the training and validation for the InceptionV3 of accuracy (left) and loss (right) curves. The accuracy curve increases steeply towards the maximum after a couple of epochs while the loss curve goes down to a minimum and remains so low after some epochs. The percent difference between the training accuracy and the validation accuracy shows little overfitting, proving that the model has been trained well and should generalize well therefore being a good model.

4.3.6 Performance and Comparative Analysis

The performance of VGG19 and InceptionV3 models will be analyzed using metrics such as accuracy, precision, recall, and F1-score to evaluate their effectiveness in groundnut leaf disease classification. A comparative analysis will highlight the strengths and limitations of each model, identifying the most suitable architecture for this application.

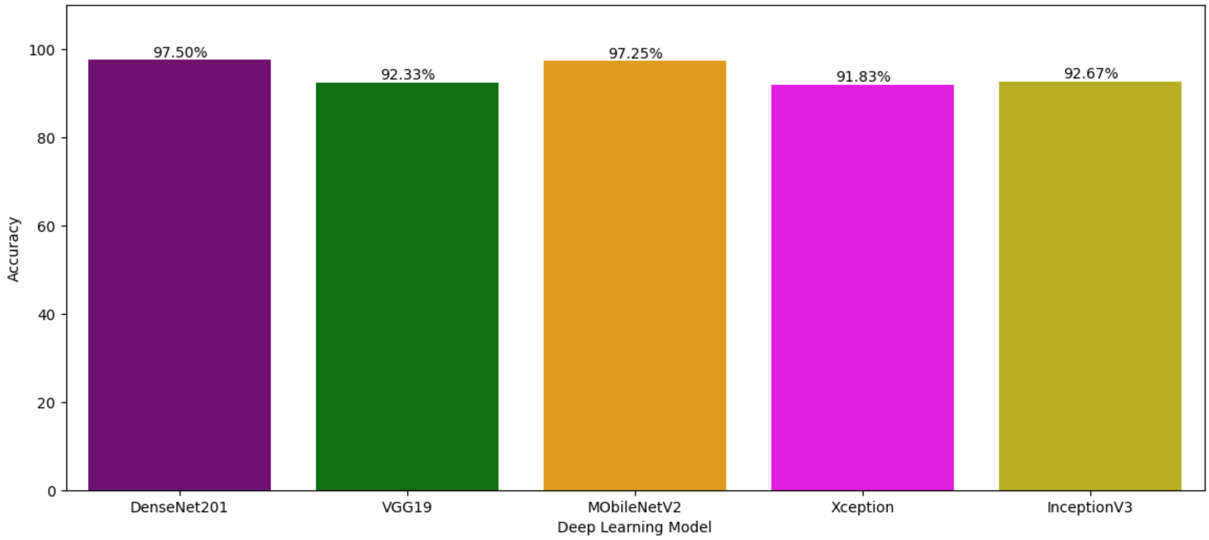

Figure 4.11: Comparative Model Accuracy Bar Plot

The bar chart 4.11 compares the accuracy of five deep learning models: therefore, there are five fundamental classes of deep network; DenseNet201, VGG19, MobilenetV2, Xception, and InceptionV3. Comparing the performance of the models, we found that the DenseNet201 model offers the highest accuracy of 97.50 percent while MobileNetV2 has an accuracy of 97.25 percent. The accuracies of inceptionV3 and VGG19 are moderate that is, 92.67% and 92.33% respectively. Xception produces an accuracy of 91.83% which is the lowest among all the models. This visualization also reveals that DenseNet201 and MobileNetV2 offer better results for the given task which without doubt guarantees a high usefulness against the other models.

4.4 Summary

The classification model exhibits strong performance in detecting five groundnut leaf disease categories: Early and Late Leaf Spot, Alternaria Leaf Spot, Healthy, Rosette, Leaf spot, and Rust. From the confusion matrix Rust is 100% accurately trained, Rosette 98% accurately, and Healthy leaves 97% accurately classified. Another is the Alternaria Leaf Spot and it has given 96% of accuracy." Minor misclassifications are recorded but it is common for Early and Late subtypes of Leaf Spot to be mislabeled as Alternaria Leaf Spot and the Healthy class. These errors suggest problems with the effort to differentiate one disease from another when dysphasic signs are subtle and the pathognomonic signs of the disease cannot be identified. Nevertheless, early identification of Early Leaf Spot and Late Leaf Spot is fairly accurate at 95%. In all, the framework is observed to attain a very high level of precision and consistency thus validating the transfer learning in agriculture. Some elaborations of the misclassification problem include managing the problem through expanded datasets or superior feature extraction can be considered a good improvement for the system and can be a beneficial aid for the farmers to examine the diseases before they progress and secure a better prognosis.

Chapter 5

Engineering Standards and Design Challenges

5.1 Compliance with the Standards

It is important that the requirements demanded by the well-known engineering standards be met in order to design a correct, effective, and long-term system. It complies with general software, hardware, communication, technology, legal, and ethical standards at the international level. All of these standards not only optimize the effectiveness of the system on which they are implemented but also address the issues of compatibility, protection, and easiness of use for the parties involved.

5.2 Impact on Society, Environment and Sustainability

The impact of utilizing the transfer learning-based system for the identification of the type of groundnut leaf diseases has a great impact on society, the environment, and sustainable farming practices. Overcoming shortcomings and achieving sustainable goals in food production, protection of natural resources, and distribution of efficient and optimized technologies, the project adapts IoT to agriculture.

5.2.1 Impact on Life

The proposed system greatly improves farmers, various related industries, as well as buyers. As a result of early diagnosis of the diseases on groundnut leaves, it assists the farmers in scaling down some of the losses and enhances the quality of the crop yield that they produce; which in turn contributes greatly to their economic welfare. Being able to afford diagnostic materials and to have accurate diagnosis limits reliance on organic identification of diseases and brings in technology-enhanced solutions for application in the farmers' fields even for the young farmer markets. In addition, this innovation also helps to bring food security since agricultural food failures will not frequently come to harm the food chain around the world.

5.2.2 Impact on Society and Environment

The project brings societal value by leveling the field and providing small farmers with better technology than most large-scale farmers. It also enlightens farming communities on the use of technology as a way of reducing isolation technology-wise. Environmentally, the system cautions against the unnecessary spraying of pesticides and fungicides through ramped-up accuracy in the process. Environmental degradation such as soil and water pollution and negative effects on non-target species are avoided by targeted therapies attained through correct disease diagnosis. The system also minimizes crop losses due to pests and diseases and thus has an unlink effect of limiting expansion into farmers' fields thus conserving forests and other natural end habitats.

5.2.3 Ethical Aspects

There emerged some major ethical issues with the kind and it appears that the system addresses them quite satisfactorily. It helps avoid the emergence of a digital divide, the matter being that there are technology guarantees for all people regardless of socioeconomic status. The system respects users' privacy and follows modern regulation norms like GDPR for appropriate data processing of any user or farm data. This kind of transparency makes sure that the users of the system do not have to be misled and thus makes sure that the misuse is also checked. The system interacts with various farmers thus the recommended yields are credible and good for the agriculturalist since it is scientific and ethical.

5.2.4 Sustainability Plan

The sustainability plan focuses on environmental, economic, and operations sustainability. The use of transfer learning minimizes computational needs, which allows the models to be trained and to run with efficiency on less energy. The system is flexible and thus can be extended to other crops and agricultural areas with little adjustments. The incorporation of frequent updates as new feedback and data are obtained will also increase its comprehensiveness in the future. There is an aspect of sustainability where the project aims at supporting efficient forms of farming without wastage and hence can support sustainability standards set by the world.

5.3 Project Management and Financial Analysis

The project follows a structured management approach, divided into key phases: pre-acquisition data gathering and data cleansing, model building, assessment, and application. Adaptive means used in agile methodology include various enhancements to feedback collected to prevent repetitive activities. They also have organized structures with specific teams on data set management, algorithm team, testing team, and deployment team. The time frame taken is 6–8 months with the following steps data preparation, training, testing, and deployment phases. The project management timeline is given in Figure 5.1:

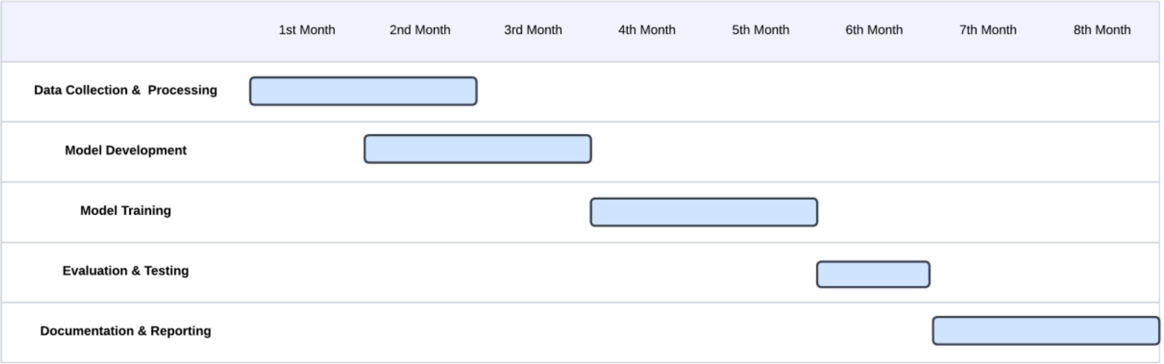

Figure 5.1: The project management timeline

The estimated project budget includes costs for:

Table 5.1: Estimated Cost

SN	Components	Estimated Cost (BDT)
01.	Hardware	1500
02.	Software and Tools	8500
03.	Data Collection and Processing	12000
04.	Documentation and Report Writing	1500
05.	Miscellaneous	1500
06.	Contingency	2500
Total Estimated Cost		27,500

5.4 Complex Engineering Problem

The project entails constructing an innovative engineering solution for diagnosing and categorizing groundnut leaf diseases using machine learning algorithms. This problem is a combination of several aspects of agricultural engineering, computer science, and environmental protection; therefore, competent implementation requires different skills and knowledge. The challenges are as follows: First, coping with big data; second, the development of effective algorithms for disease diagnosis; third, effective incorporation of the system in farming with emphasis on environmental and societal factors.

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 Stakeholder Involvement	EP7 Interdependence
√	√	√	N/A	N/A	N/A	√

EP1: Dept of Knowledge

Computer Science, Agriculture, Data Science.

EP2: Range of Conflicting Requirements

Balancing accuracy with computational efficiency, interpretability vs. performance, and real-time applicability.

EP3: Depth of Analysis

Deep analysis of machine learning models, disease classification algorithms, and data preprocessing techniques.

EP7: Interdependence

High interdependence between machine learning models, agricultural domain knowledge, and computational resources (hardware limitations).

5.4.2 Mapping with Knowledge Profile for EP1

Table 5.3: Mapping with Knowledge Profile

K3 Engineering Fundamentals	K4 Specialist Knowledge	K5 Engineering Design	K6 Engineering Practice	K8 Research Literature
√	√	N/A	√	√

K3: Engineering Fundamentals

Understanding of machine learning fundamentals and image classification techniques.

K4: Specialist Knowledge

Knowledge of plant pathology, agricultural practices, and crop disease management.

K6: Engineering Practice

Practical experience in model implementation and deployment in real-world agricultural settings.

K8: Research Literature

An extensive review of research papers, case studies, and existing solutions for agricultural disease classification and machine learning applications in agriculture.

5.4.3 Engineering Activities

Table 5.4: Mapping with complex engineering activities.

EA1 Range of resources	EA2 Level of Interaction	EA3 Innovation	EA4 Consequences for society and environment	EA5 Familiarity
√	N/A	√	√	N/A

EA1: Range of Resources

The project requires diverse resources, including:

- Data Resources: The groundnut leaf dataset includes images of both Healthy and disease-stricken leaves that must be correctly observed by the model. Other data augmentation methods increase the size of such a dataset, as far as providing the necessary solidity and accuracy.
- Technological Resources: Deep learning models including VGG16,

ResNet50, MobileNetV2, TensorFlow, and Keras tools are then used for model training and model execution. Cloud computing services guarantee scalability and proper training processes.

- Human Resources: Special focus needs to be placed on areas of agriculture, data science, and software engineering to achieve improved results. They enter the resource-sharing process to guarantee an accurate problem-solving approach based on the required fields.

EA3: Innovation

Transfer learning is another novel feature incorporated in this project since it involves using pre-trained models intended for agricultural use thereby shrinking large computational power and data requirements. It means that the mentioned approach guarantees the possibility of establishing a system that is flexible enough to function effectively with rather different kinds of crops and in various regions. Standardization of augmentation procedures including rotation and horizontal flipping leads to the improvement of dataset and model quality. Neural networks' application combined with pertinent agricultural knowledge creates a successful connection between AI and actual issues making this an innovative approach to machine learning.

EA4: Implication for Societies and Environment

The project has significant societal and environmental benefits:

- For Society: It promulgates the availability of sophisticated technologies to advance farming and increase yields and low incidences of loss among small farmers. This promotes economic stability and the viability of farming businesses.
- For Environment: The system reduces cases of ineffective pesticide and fertilizer application because it reduces the risk of broad application due to misdiagnosis of the diseases. This has led to less chemical leaching, soil depletion, and impaction of organisms other than pest-espoused sustainable farming methods.
- It also addresses general issues such as food security by maintaining good and stable yields and improving the quality of agriculture.

5.5 Summary

The activities involved in the formulation of the groundnut leaf disease detection system are explained in this section and then aligned to the engineering activities that include the use of resources, innovation, and societal/environmental effects. With the concept of transfer learning and further innovative data augmentation as the core techniques of the project, innovation in agricultural technology is depicted. Effective in providing real value to farmers, effective in resource conservation, and helps to solve the problems of present society including food insecurity and inequalities. The utilization of multiple resources and the examination of the system's more extensive consequences amorphously demonstrate the potential of this project as a multifaceted, interdisciplinary challenge, which is quite relevant to Table 5.4 Mapping with complex engineering activities.

Chapter 6

Conclusion

6.1 Summary

The more concrete contribution of this research work is on the assessment of a system designed based on transfer learning in the identification of diseases, as well as their categorization on groundnut leaves. Finally, due to the availability of a reliable data set of high quality, the system offers a high level of accuracy and reliability with the help of VGG19, InceptionV3, MobileNetV2, Exception, and DenseNet201 pre-trained models. These methods assist in enhancing data augmentation because the model will easily handle change and be generalized in reality. The developed solution is in the form of an effective and easily manageable form for farmers; that will prevent them from incurring massive losses due to diseases and facilitate ecological farming. In addition to this, it also tackles global problems such as hunger since it does not use any material in the processing of products including supporting precision farming.

6.2 Limitation

Even though the simplicity and effectiveness of the system have been observed the following limitations are evident. However, the given dataset after augmentation could not capture all possible presentations of diseases in different environments. The prediction of some models could also be influenced by previous training models which may originate from bias in the training data sets of the former models. Besides, the management of the system requires computing facilities which may be a problem of scope in the extended farming areas in the developing world. There is no financial or personal interest or affiliation of the authors concerning this study. All the researches were conducted very clearly and only the intention to help the farming society and to make the practices better was present. Thus, with the elimination of these limitations and expansion of the scope of the proposed system, it has a perspective of becoming a top-level system for diagnosing agriculture and ensuring further successful advancement of farming communities worldwide.

6.3 Future Work

It also means that this current system can be used as the fundamental ground for more research and development in robotics in the future. Future work can explore the following areas:

- Expansion to Other Crops: Applying the currently used system of identifying diseases that affect other crops for other issues affecting agriculture.
- Incorporation of Multispectral Imaging: The coordination of data originating from one or more multispectral or hyperspectral images in order to increase the levels of accuracy of disease identification.
- Real-Time Mobile Application: Exposing the farmers to the application to assist them use the system if they are in the field, to make diagnosis quicker and easier.
- Integration with IoT Devices: To continuously integrate, the system with IoT experiences-based sensors for monitoring the crops and condition rate.
- Advanced Model Architectures: Looking at other revolutionary architectures such as Vision Transformers and working towards enhancing the classification outcomes.
- Regional Adaptations: The fact that disease peculiarities and different farming practices require modification to improve application specificity at different places.

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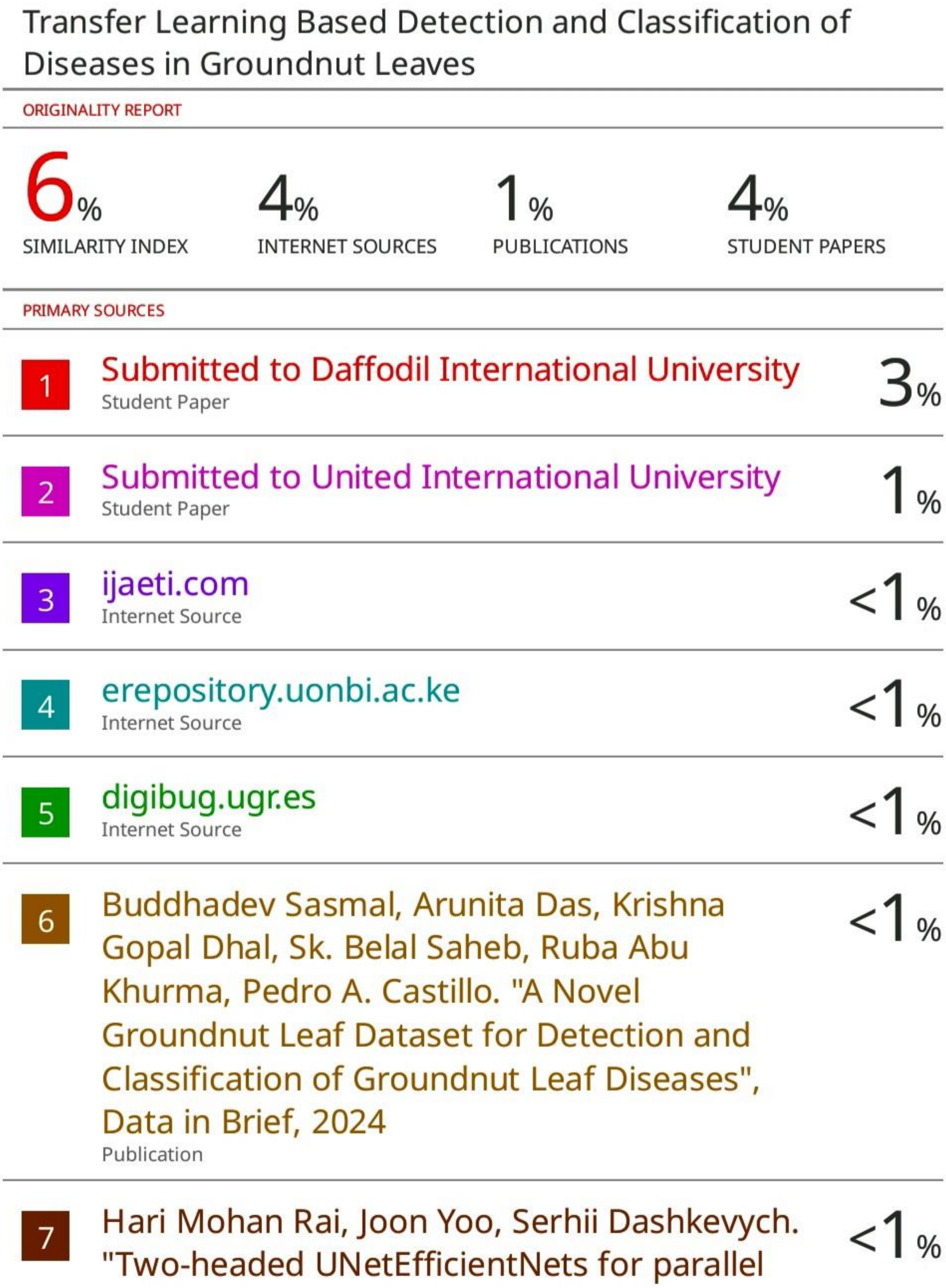

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