AN ADVANCE DEEP LEARNING APPROACH FOR RICE LEAF DISEASE CLASSIFICATION

BY

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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 **"An Advance Deep Learning Approach For Rice Leaf Disease Classification"**, submitted by **Muhammd Saifullah** to the Department of Computer Science and Engineering (CSE), Daffodil International University (DIU), 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 July 14, 2024

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Finally, I must acknowledge with due respect the constant support and patience of my parents.

ABSTRACT

Feeding the people and preventing the spread of diseases among crops depend on the early diagnosis of diseases in agricultural crops. This paper employs transfer learning to automate the classification of rice leaf diseases, particularly those common in the area as bacterial leaf blight and brown spot. In order to assess the effectiveness of the aforementioned Deep Learning (DL) models, a dataset including 692 photos of brown spots, 700 photographs of healthy rice, and 700 images of bacterial leaf blight is employed in the vicinity of the Pabna Bangladesh Agriculture Development Corporation (BADC) & Jamalpur district paddy field. Data collection, sample preparation, labeling, image processing, selecting the best model, training, and testing are all included in the established technique. The models over fit and produced varying accuracy rates, with DenseNet201 and MobileNetV2 recording 98.89% and 98.57%, respectively, according to the findings analysis. The findings are discussed with a focus on model architecture and choice as crucial elements in the success of disease classification. The anticipated future efforts will focus on investigating imbalanced categorization and ensemble learning. To sum up, this study contributes pertinent knowledge to the advancement of automated disease identification in agriculture, which is important for global food security.

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CHAPTER 1

Introduction

1.1 Overview

Rice is an important food crop for a large part of the world population; therefore, it is important that the health and productivity of rice crops are maintained. But rice is susceptible to several diseases like rice brown spot and rice leaf blast that result to variation in the unit as well as the quantity of rice produced. These disorders should be detected as early as possible and correctly classified to ensure appropriate management of the disease. Conventional techniques for disease identification involve using the naked eye and are recognized as time-consuming, labor-intensive, and subjective, as they are implemented by agricultural qualified individuals. Moreover, the competency essential for accuracy in diagnosis might not be available in all areas, including the rural ones. Traditional disease detection methods depend primarily on visual inspection by agricultural qualified individuals, which can be time-consuming, labor-intensive, and subjective. Furthermore, the competence required for correct diagnosis may not be available in all regions, especially rural areas.To overcome these issues, computer vision and machine learning approaches present promising options for automated disease identification and classification in rice crops. Transfer learning, a deep learning methodology, has emerged as an effective method for using trained neural network models to perform new tasks with less labeled data. In this paper, I present a transfer learning technique to rice leaf disease classification, with the goal of effectively identifying and classifying common diseases including rice brown spot, rice leaf blast, and healthy rice leaves. Using pretrained convolutional neural network models trained on large-scale picture datasets, we hope to apply the learnt representations to the specific problem of rice leaf disease classification. The methodology consists of data collection, labeling, image processing, model selection, training, assessment, and testing. I collected a collection of rice leaf photos, classified them with disease classifications, then preprocessed them to standardize the format and increase dataset variety. We chose advanced pretrained models such as DenseNet201, InceptionResNetV2,VGG16, VGG19, and MobileNetV2 for transfer learning. These models have been improved using the

labeled dataset to learn discriminative characteristics for illness categorization.
I hope that my work will help to develop automated methods for rice disease management, allowing for early identification and action to ensure global food security and sustainable agriculture.

Deep Learning Model

DenseNet201, InceptionResNetV2, VGG16, VGG19, and MobileNetV2 are some of the deep transfer learning models that are very essential to your thesis on rice leaf disease classification because they have pre-trained architectures that will help to extract features from the images. The models have been pretrained on large scale ImageNet dataset which encodes different aspects of images that can be effectively transferred to related tasks with less amount of data as in case of this rice disease classification. Because of their depth, complexity, and a variety of chosen architectural designs, they can focus on detailed aspects of rice leaf images and improve the disease classification's accuracy and resilience.

In my thesis paper I am using five Deep Transfer Learning Model. In Given below I am describing those models:

DenseNet201

A very deep convolutional neural network called DenseNet201 was created with a dense connection architecture in which every layer map feeds every mapping from the layer before it. It enhances feature propagation and encourages feature reuse, which contributes to its great efficacy in extracting complex patterns from images, such as disease-affected rice leaf patterns. DenseNet201's ability to construct such exact and complicated correlations between features is crucial for the task of classifying rice leaf diseases into seven groups, which comprises the fundamental thesis. Transfer learning is made possible by pretrained weights that come from a training onset on huge datasets like ImageNet; this feature is especially helpful when working with relatively modest agricultural datasets. With the integration of DenseNet201, classification, classification

Accuracy can be significantly increased with the goal of distinguishing and early diagnosing rice illnesses. As a result, if you include it in your thesis, it provides the proper framework for an effective disease diagnosis, which will improve precision agriculture and crop management.

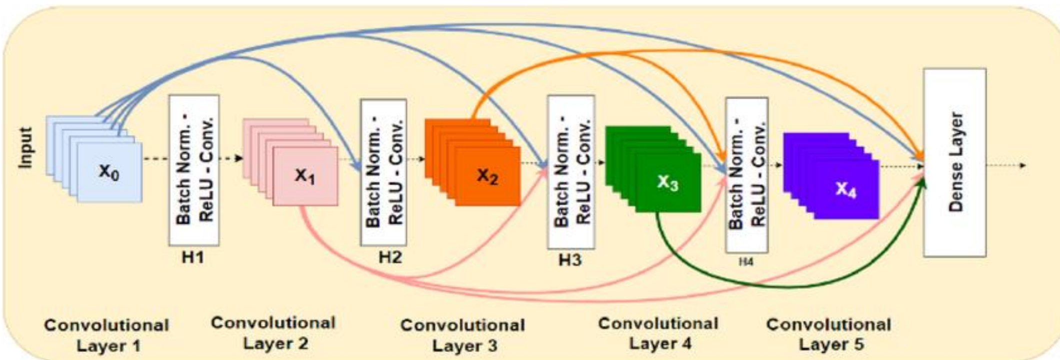

Figure 1.1.1: Densenet201 Architecture G. I. Kimet al.2023[21]

InceptionResNetV2

The network has components from both the ResNet and Inception architectures, combining them to create InceptionResNetV2. The indication of how the core methodology of the thesis is responsible for the effective extraction of the hierarchical characteristics from the rice leaf image is crucial. For computational efficiency, the input to the model's initial modules must essentially consist of many scales of the same feature running concurrently. This helps identify subtle changes and patterns in rice leaves that may be signs of disease. Additionally, InceptionResNetV2's residual connections make it possible to train extremely deep networks and avoid the vanishing gradient issue, which makes it possible to learn as many different disease features as possible using a limited amount of agricultural data. learning on the ImageNet dataset, Due to its great transfer learning capabilities, InceptionResNetV2 is essential for achieving high accuracy while using a very limited dataset for disease diagnosis. Thus, adding InceptionResNetV2 to the thesis framework ensures that you have a strong system for automatically identifying harmful rice illnesses, improving crop health management and sustainable agriculture.

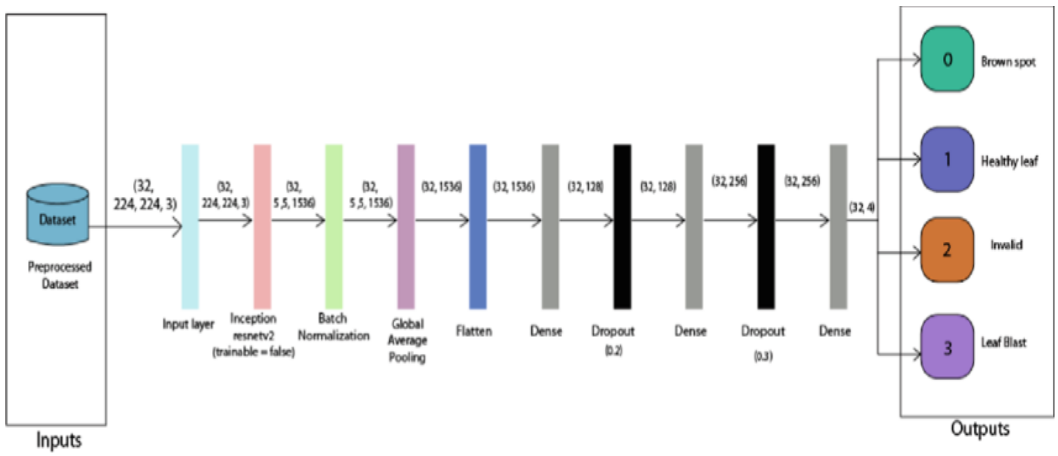

Figure 1.1.2: InceptionresNetV2 Architecture Abdullah Al Munemet al.2022[22]

VGG19

One of the deep convolutional neural networks, VGG19, is well-known for being both extremely effective and straightforward when it comes to handling image categorization issues. The depth of this architectural design, which consists of 19 layers with tiny 3 x 3 convolutional filters that enable the rice leaf images to pick up the relevant nuances and hierarchical aspects, is what determines how significant it is to your thesis. The VGG19 model is the best to serve as a baseline for comparison with other models and is also helpful to comprehend the differences between other models because of its simpler design than other more complex models, which makes it easier to implement and less ambiguous to interpret understand the concept of feature extraction for Agricultural pictures. Additionally, transfer learning is made simple by using pretrained weights from models like VGG19, which was trained on sizable datasets like ImageNet. Given the lack of annotated data, this capacity is particularly important for utilising prior knowledge in order to improve the classification accuracy of rice leaf diseases. Consequently, VGG19 plays a crucial role in your thesis since it provides a firm foundation for directing and developing automated disease detection in rice farming, which supports sustainable agriculture.

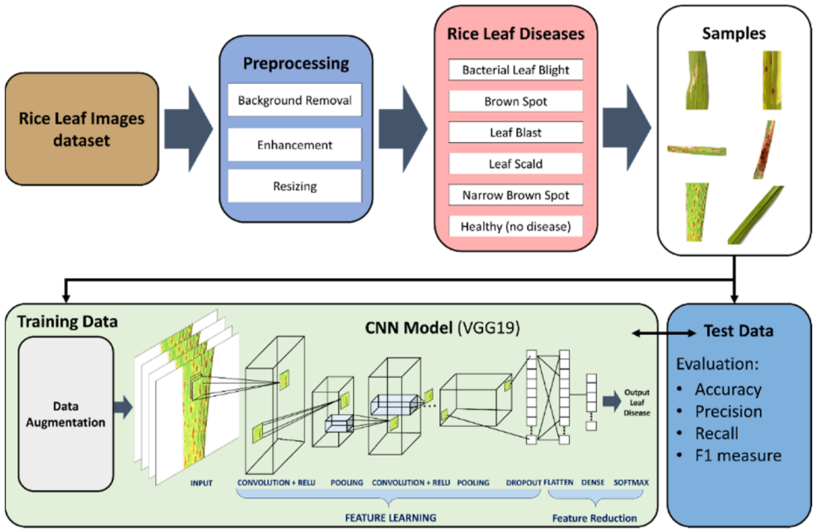

Figure 1.1.3: VGG19 Architecture G. Latifet al.2022[23]

VGG16

Deep convolutional neural network VGG16 is quite basic, but it excels at image recognition tasks. The architecture you stated, which has 16 layers, tiny 3x3 convolutional filters, and max-pooling layers, demonstrates its significance to your theory. Because of the VGG16's structure, the network can extract minute details and patterns that are typical of photos of rice leaves, which is crucial for illness diagnosis. Since VGG16 was trained on millions of images from datasets like ImageNet, weights related to rice leaf diseases can be transferred, facilitating detection even with a small number of annotated photos.We may always use VGG16 as a benchmark for validating and comparing more complex models, such as DenseNet201 or InceptionResNetV2, that are required for your thesis work because of its straightforward design and already achieved high standards. By using VGG16, your research can achieve a high recognition rate and identify areas of interest in the field of automated disease diagnostic systems applied to agriculture, which can lead to improved crop management and environmentally friendly practices.

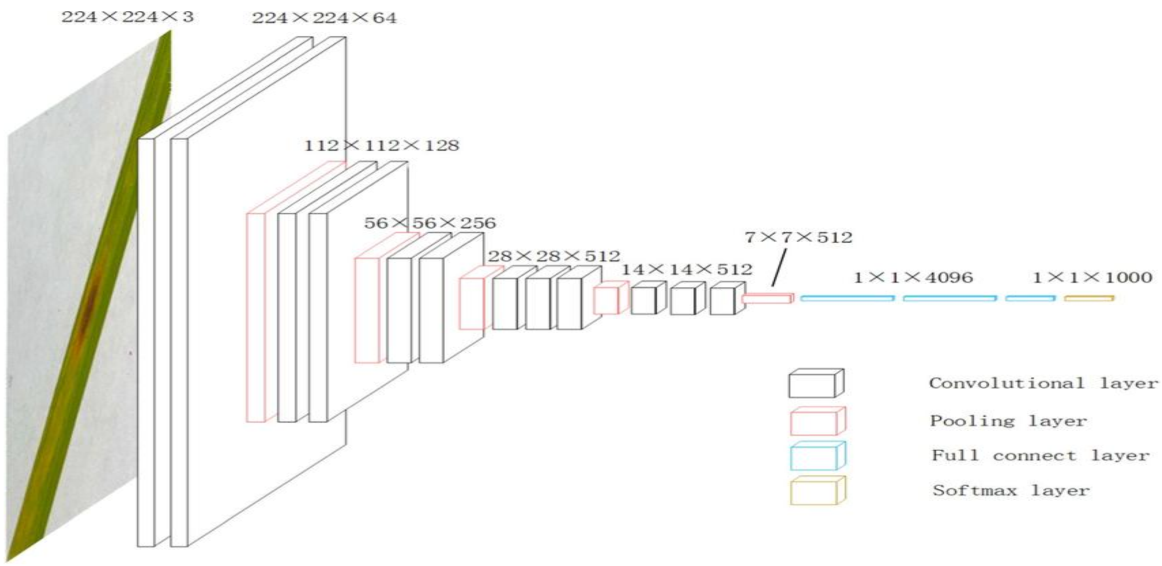

Figure 1.1.4: VGG16 Architecture Y. Lü, X. Taoet al.2023[24]

MobileNetV2

Your thesis on the categorization of rice leaf disease benefited greatly from the use of MobileNetV2, a lightweight convolutional neural network that was specifically designed for mobile and embedded vision applications. This is because of its effective architecture, which makes it suited for deployment in agriculture-based settings with modest hardware and takes little in the way of processing resources and time when producing forecasts. In order to run on low-profile hardware, MobileNetV2 maintains state-of-the-art accuracy while minimizing model size and processing requirements. They expand transfer learning features and are pre-trained on datasets like ImageNet, which enables them to swiftly hone in on the necessary task, such detecting rice leaf diseases. It is implied that MobileNetV2 is a very helpful instrument in assisting farmers and crop evaluators in taking timely measures towards the crops and improving their management because of its ease of deployment in the actual world, particularly in the field where certain actions must be made in real-time. You can address the large-scale solutions that attempt to automate the process of disease identification, hence boosting agricultural sustainability and food security, by include MobileNetV2 in the thesis.

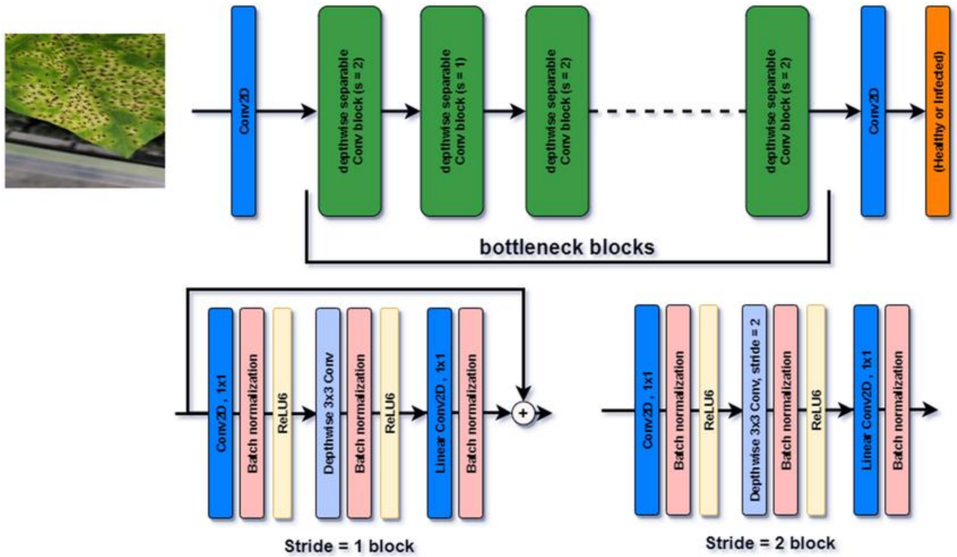

Figure 1.1.5: MobileNetV2 Architecture F. Shahoveisiet al.2023[25]

1.2 Background and Present state

Production of rice is crucial to the security of the global food supply because it is a staple food for more than half of the world's population. However, a variety of ailments can have a negative impact on rice harvest quality and productivity. Using traditional methods, experts have to hand inspect rice leaves to diagnose faults, which is labor-intensive, time-consuming, and prone to human error. With the advancement of cutting-edge technology, more and more people are interested in applying deep learning for automated disease identification and classification. Deep learning, a type of machine learning, uses neural networks to learn from large datasets and generate accurate predictions. It has shown to have enormous promise in several sectors, including agriculture, where it can help The application of deep learning to the classification of rice leaf diseases is still being researched and developed. Several studies have demonstrated the accuracy with which convolutional neural networks (CNNs) and other deep learning architectures can classify illnesses affecting rice leaves. With promising outcomes, scientists have developed models in the lab that were trained on enormous datasets of annotated images of rice leaves. Based on visual signals in photographs, these models can identify and distinguish between a wide range of diseases.

1.3 Problem Statement

Timely identification of diseases on the rice leaves is important in avoiding losses and feeding the nation. Previously employed detection methods are sophisticated and time consuming and persons with adequate information expertise are needed for their application. The objective of this research is the automatic classification of the two rice diseases, namely the brown spot and bacterial leaf blight, through the use of transfer learning. The performance metric that would be targeted is accuracy in an attempt to identify the disease in the crops in achieving this, some of the limitations to expect include over fitting and the imbalanced data will be worked around by developing an efficient and scalable method for agricultural use.

1.4 Objectives

The objective of this study is to design and assess an intelligent system for the differentiation of rice leaf diseases with the aid of deep learning methodologies known as transfer learning with MobileNetV2 and DenseNet201 networks. Thus, the study aims to use modern techniques to improve the methods of diseases identification and to contribute to sustainable agriculture development. The general aim is to equip the farmers with functional diagnostic tools that will increase chances of identifying diseases on crops early enough to help in management of crops to avoid food insecure. Through the use of sophisticated neural network models, rice leaf classification using deep learning aims to effectively identify and classify diseases like bacterial blight, brown spot, and blast based on visual symptoms extracted from images of rice leaves. By automating the process that was previously dependent on manual inspection, the approach aims to achieve high accuracy and reliability in disease diagnosis, enabling early detection and timely intervention to minimise crop losses. Scalability is a key goal, ensuring the models can efficiently handle large datasets and diverse environmental conditions, making the technology accessible to farmers and agricultural professionals. Empowering farmers

1.5 Proposed Solution

This work presents an application of transfer learning that aims at developing an automatic system to classify rice leaf diseases with primary emphasis on brown spot and bacterial leaf blight. The images will be preprocessed and annotated then brought into train MobileNetV2, DenseNet201. As an extension of these models, the system further intends to maintain a high level of efficiency in classifying the diseases. Overfitting will be reduced with the help of some practices including data augmentation. The performances of the models will be assessed so that enhancements will be identified to make them stronger, more efficient and conducive to accommodate an overwhelming number of patients to detect diseases.

1.6 Scope and Limitations

Using image-based diagnosis approaches, an enhanced deep learning approach to rice leaf disease classification can recognize and categories a variety of common rice leaf diseases, including bacterial blight, brown spot, and blast. Large labeled picture datasets are used in this method to train neural network models, resulting in strong generalisation and learning. In addition to offering real-time or almost real-time illness detection and scalability to manage a huge number of photos and users, its goal is to interface with mobile and web applications for easy access by farmers and agricultural professionals. Nevertheless, the method has drawbacks, including reliance on the caliber and accessibility of training data, fluctuations in the surrounding environment impacting image quality, and difficulties differentiating between illnesses with comparable visual symptoms.

1.7 Report Organization

The proposed report follows a systematic format of presenting information that orients viewers through the research procedure, conclusions, and recommendations. Every chapter has its role and contributes to the perceived cohesiveness and richness of the document as a whole.

Chapter 1: Introduction.

In this method, the researcher gives an introduction to the general research topic, aims and reasons for conducting the study. Provides an overview of the research topic and the research problem as a whole.

Chapter 2: Literature Review.

Summarize the findings from the pertinent literature, theoretical frameworks, and prior research on rice leaf disease categorization, transfer learning, and computer vision methods.

Chapter 3: Research Methodology

Explains how data were collected processed, the selection of models, how models were trained and how the study evaluated those models.

Chapter 4: Implementation

Summarizes the overall Implementation procedure.

Chapter 5: Result and Analysis

Summarizes the overall experimental outcomes and shows the performance results and comparison of transfer learning models along with accuracy of classification

Chapter 6: The Impact on Society

Outlines how the study could benefit society and how the discussed results could be used to make conclusions about disease diagnostics when it comes to agriculture with the primary focus on pests.

Chapter 7: Conclusion

Concludes with the results and implications of the research and offers suggestions for areas of future research, while also emphasizing the significance of the study's findings for the fields of agriculture and computer vision.

1.8 Summary

The primary goal of this work is to contribute to the pressing issue of accurate and fast identification of rice leaf diseases like brown spot and bacterial leaf blight with the help of transfer learning. To construct an efficient and reliable automated classification system, using MobileNetV2 and DenseNet201 deep learning models is proposed.The expected result will be a marked increase in the accuracy of disease discrimination and thus timely prevention measures that will lead to increased Agricultural production and Food Security. The subsequent sections will provide a discussion on the application of the described methodology, the outcomes of this strategy, and the likelihood of deep learning in transforming agricultural diseases' diagnosis and prevention management.

CHAPTER 2

Literature Review

2.1 Overview

The over one-half of the world's population depends on rice as a staple food, and this means that cultivation of this crop is critical to feed the world's population. On another note, rice plants are susceptible to several forms of diseases for instance the brown spot and bacterial leaf blight leading to great yield loss. The existing approaches in disease detection are costly, repetitive, highly depends on expert opinion, and are not suitable for mass production. In recent years, realizing methods based on deep learning (DL) is another efficient approach to automated solutions. Transfer learning, which is a technique of DL, means that pre-trained models may be employed to improve disease identification's preciseness and speed. In this particular research, transfer learning is used in the identification of rice leaf diseases, with an end-result in designing a foolproof, efficient, and fast diagnostic tool. Using a sample of 2,092 images collected from Pabna BADC & Jamalpur district paddy field, this study compares the effectiveness of MobileNetV2 and DenseNet201 models with the intention of enhancing the management of diseases affecting crops for enhanced production of crops for the people in need.

2.2 Related Works

The literature review includes a critical analysis of all research and / or scholarly works that are related to the study. Thus, the present review reflects the state of prior research and contributes valuable insights as well as a theoretical background for the current study. In this case, it assists in defining areas underrepresented in research, pointing out emerging trends and informing a study's design. A literature review mapping of peer reviewed articles, books and other related sources help in attaining a basic orientation of the substance under investigation and also assists in direction of the study.

As given below, I am writing a similar paper review, which will help me more:

Malathy, S., et al. utilized a fuzzy logic and deep learning-inspired optimization approach to effectively categorize plant diseases. Pre-processing uses Region of Interest extraction while segmentation uses Deep Fuzzy Clustering; for feature extraction, various methods are used which are statistical and CNN features. Signifying glorious performance metrics, the recommended RHGSO-based deep learning system expounds its utility in plant disease categorization attaining the best accuracy, sensitivity, specificity, and F1-score of 0. 9304, 0. 9459, 0. 8383, and 0. 9142, respectively.Jiang, Feng, et al taked photos of rice leaf disease are described as follows: Due to the inclination of CNNs, the overall takes photos of rice leaf disease are first passed through the CNN process for feature extraction and afterwards the SVM approach is implemented for classification.The identified SVM model uses gamma = 50 and C = 50 as well and has an astonishing average accurate identification rate of 96. In the first case, the results of the Hepatitis study showed that the classification error was reduced by 8% using optimization measured by correctly classified rate through 10-fold cross validation. This level of accuracy, the most achieved according to the study, demonstrates just how effective the interaction between deep learning and the SVM technique is to put a name to rice disease.Upadhyay, Santosh Kumar, et al. The CNN based technique proposed by deals with the identification of three common diseases of rice namely bacterial leaf blight, brown spot and leaf smut. The intended procedure, which was learned from 4000 picture samples of healthy and diseased rice leaves, achieves a jaw-dropping accuracy of 99. A precision rate of 7% was achieved on the dataset and demonstrated the speed and efficiency of the diagnostic system in identifying diseases. It also shows that for the categorization of rice diseases the fully linked CNN model is stable at its greatest accuracy that was recorded by the study.Shrivastava, Vimal K., et al. adopted a set of 619 real field photographs depicting the symptoms of four sets of rice plant diseases: Rice Blast, Bacterial Leaf Blight, Sheath Blight, and Healthy Leaves. The proposed model achieves a 91 % test accuracy because it combines a support vector machine classifier with features obtained from a deep neural network that is pretrained on ImageNet. 37% classification accuracy. which is testified as the most accurate approach in the research, is rather engaging, but illustrates the efficiency of the combined CNN-SVM approach in classifying rice illness as well.Ammar Kamal Abasi et al., initiated a Convolutional Neural Network (CNN) model that offers a marvelous accuracy of 91%. Actually, it reduced to as low as 4 percent during the last epoch. The suggested method can be considered efficient far critical identification of rice leaf diseases as it defines lesser loss and standard overfit as compared to the Transfer Learning Inception-v3 and Transfer Learning EfficientNet-B2 models. This accuracy, which is the highest in the research, indicates how effectively the proposed CNN model is in the classification of rice diseases on the leaves.Specifically, Sharma, Rahul, et al have design a CNN model that was found to deliver high accuracy values of 99. 47% for bacterial blight of pigeon pea, 58% for rice-leaf diseases, and 97% percent for control of Thrips, respectively. In the case of potato leaf diseases fresh BMV-HIV+ cotton plants were used elicitors 66% efficacy. The model excels other classifiers from machine learning technics such as SVM, KNN, Decision Tree, and Random Forest in discovering the underlying raw images. Instead of applying deep CNN from the scratch, Hasan, Md Jahid, et al. integrated an SVM classifier with the AI model through transfer learning, more enhancing its performance up to 97. 5 percent at the end of this training when using a database of 1080 photos of nine rice diseases. The photos were from the Rice Leaf Disease Dataset whereby gent authors such as Patidar, Sanjay, et al. labeled diseases in rice plants as Brown spot, Leaf smut, and Bacterial leaf blight. The ResNet model attained the highest accuracy of about ninety-five percent while the other classifiers were faster and more efficient, making ResNet the top classifier among them. 83%. Both CNN and ResNet models are revealed to be efficient means of predicting plant leaf diseases and their types. Meenakshi Aggarwal, et al., used deep learning algorithms and ensemble learning classifiers for the detection of diseases in rice leaves and It was found that the detection rate of the model was 94 percent. The method extracts features from pre-trained models and organizes the pictures of diseases, such as bacterial blight, blast, and brown spot. The proposed model gives better performance than the existing techniques in terms of the accuracy, recall rate, F1-score, Matthew's coefficient, and Kappa statistics. That is why, Krishnamoorthy, D., et al. offered Inception-ResNet-v2 which is known as the recognition of rice leaf diseases for practical purposes with the validation accuracy of 82% and which is significantly higher than other existing techniques. Sharma, Mayuri, et al. used VGG-16, ResNet50, and InceptionV3 deep CNNs similar to the one applied in this paper with transfer learning to identify diseases on rice plant leaves.

2.3 Comparison between existing works

From earlier research it is found that different methods have been employed for plant disease classification with focus on rice leaf diseases. Some of the researchers employ HR optimization strategies that implement the fuzzy logic along with the deep learning mechanisms, while other employ the Convolutional Neural Networks (CNNs) with the support vector machines (SVMs) for classification. Notably, the level of accuracy provided by means of these methods is high and makes up at least 91.37% to 99.7%, this is pointing the fact that deep learning paradigms are effective for diagnosing and classifying rice illnesses.

TABLE 2.3: ANALYTICAL COMPARISON WITH EARLIER WORKS

SL	Author Name	Used Algorithm	Best Accuracy with Algorithm
1.	Malathy, S., et al.	Deep Fuzzy Clustering, CNN	93%
2	Jiang, Feng, et al	CNN, SVM	96.00%
3	Upadhyay, Kumar, et al.	CNN	99.70%
4	Shrivastava, Vimal K., et al.	CNN, SVM	91.37%
5	Abasi, Ammar Kamal, et al.	CNN	91.14%
6	Sharma, Rahul, et al.	CNN	99.58%

2.4 Open Issues

The problem solved in the present work concerns the diagnostic of rice leaf diseases as well as the experimental materials and methods applied in the deep learning field based on transfer learning. Specifically, the study targets the recognition of diseases such as the brown spot and the bacterial leaf blight and healthy and affected rice leaves. More specifically, the aim is to find out the pre trained neural network models, image augmentation techniques, and that have the best prediction accuracy. Moreover, the consideration of output variations with respect to the size of the data set and the computational capability is also part of the study. Though the study specifically deals with rice leaf disease classification, the generalization of results is very vast which includes automated disease detection in agriculture and is useful in the development of precision farming in large scale.

2.5 Challenges

Some issues emerged when the rice leaf disease classification system was under implementation. This was seen to pose a problem due to class imbalance leading to poor training of the models; thus, to solve the problem, data image augmentation was used. Besides, selecting the proper pre trained neural network models for transfer learning posed a challenge due to the varying performances of the different architectures in the classification task. Besides, the tuning of the fields like learning rate and the batch size was not easy, and extra efforts had to be made to gain the best in the model. Last but not least, the generalization of the classification system to unseen data and realistic agriculture environments also acts as a big challenge since it requires accurate evaluation and validation. To address these issues, the attempted method was that the choice of methodology and the refinement process for generating the classification system had to be given adequate consideration and improvement.

2.6 Summary

In conclusion, the rice crop is important for feeding the world's population but it is vulnerable to diseases that can lead to reduced production. Conventional detection techniques are not suitable for pelagic farming at industrial level, there is need for improved detection systems. The findings presented in this research use transfer learning and deep learning approaches of MobileNetV2 and DenseNet201 to create an effective classification of rice leaf diseases such as brown spot and bacterial leaf blight. Therefore, by employing the broad set of features gathered this research is expected to improve disease identification accuracy and speed. The outcomes are expected to enhance the ways through which diseases are managed and agriculture conducted, thus enhancing the efforts for improving the food security and also worldwide agriculture sector.

CHAPTER 3
Research Methodology

3.1 Overview

This research work adopts the systematic procedure to establish an automatic rice leaf disease classification system employing transfer learning. A total of 2092 images of healthy leaves, brown spot and bacterial leaf blight affected images were taken from Pabna BADC & Faridpur district paddy field. The images used in these were pre-processed, first, to ensure uniformity in size and standardization of quality. All the pictures were identified based on the type of disease in the particular picture. Normalization, and augmentation techniques were performed to improve the extraction of the features and counteract over fitting. Therefore, for this study, MobileNetV2 and DenseNet201 models were selected because they are both accurate and computationally efficient. The models were trained on the pre-processed dataset using data augmentation to enhance the models' generalization The trained models were tested on a different test set as a way of establishing their accuracy in diagnosing rice leaf diseases This methodology has been comprehensive in ensuring the development of a disease detection system that is efficient and sustainable.

3.2 Hardware Requirement

Automated classification of rice leaf diseases is the main objective of this research relying on computer vision and machine learning with transfer learning techniques. The study's purpose is targeted toward developing and implementing an applicable model that can accomplish the task of recognizing and categorizing typical rice leaf diseases, including rice brown spot and rice leaf blast, by utilizing images taken in the agricultural environment. Thus, the study touches upon such topics as data aggregation, cleaning, feature selection, model identification, training, and assessment, with an emphasis on the utilization of prepared neural network models to enhance disease identification. This research's instruments include computational hardware and software for data analysis and model development, cameras and scanners to obtain rice leaf images, and tools for labeling and assigning classes to images and commonly used machine learning libraries. The instrumentation also encompasses pre-trained neural network models and transfer learning frameworks, along with metrics utilities for evaluating classification accuracy. Being instrumental in addressing the study's objectives and research questions, the study seeks to offer the necessary contribution to the existing body of knowledge on the application of automated systems in disease diagnosis in agriculture.

3.3 Data Collection Procedure

The dataset, which included photos of rice leaves afflicted by three different diseases, was gathered from paddy fields in the Pabna BADC and Jamalpur district: This indicates that the three classifications of the samples are healthy, bacterial_leaf_blight, and brown spot. The first raw data set is as follows: The data class imbalance issue is shown by the terms brown spot, bacterial_leaf_blight, and healthy. The created images of brown spot, which number 692, bacterial leaf blight, which number 700, and healthy, which number 700, are equalized to the through duplication and synthesis of fresh images. This was fixed by using image augmentation to enhance the dataset's data. The following models were then trained and tested using the photos in this data set. The information is all primary data. In given below there are some images of datasets and categories of images in Figure 3.3.1& 3.3.2

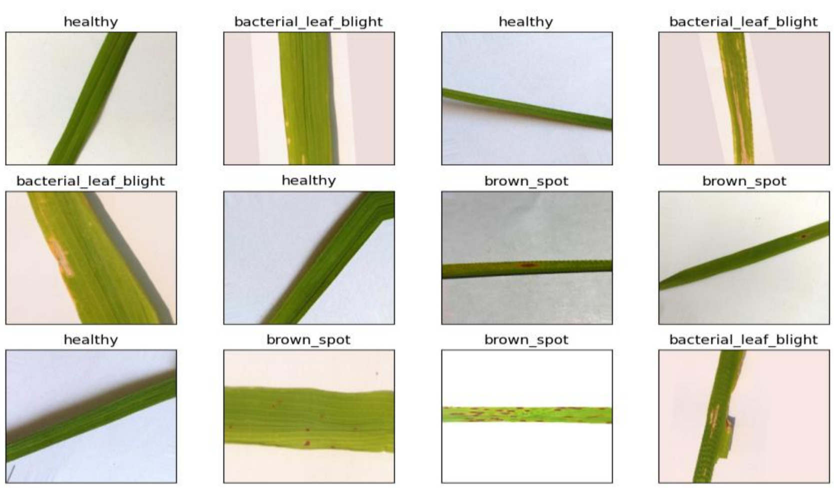

Figure 3.3.1: Dataset's Images

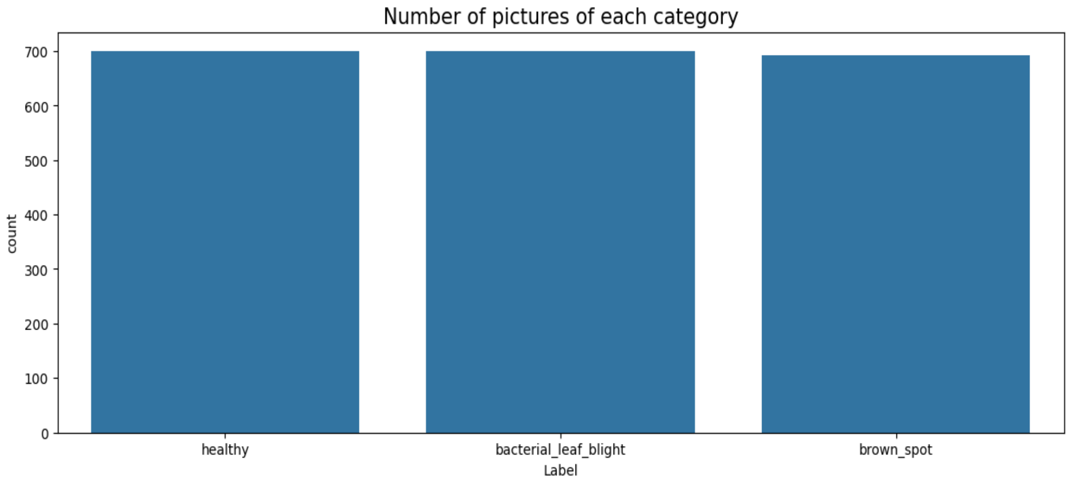

Figure 3.3.2: Number of pictures of each category

3.4 Statistical Analysis

Descriptive statistics were used in the assessment of model performance whereby the common parameters such as accuracy, precision, recall, and F1 score were calculated. Furthermore, a confusion matrix was used to complement the classification results as well as observe any possible patterns that might have led to misclassification. In the group of performance comparison, t-tests or ANOVA tests were performed to check the significance of the differences of the performance among the various transfer learning approaches. Moreover, the inference time, and the usage of the computer resources were calculated in order to assess the real-world applicability of the developed classification system. Thus, the method used in the current research targeted at offering quantitative analysis of the classification system's efficiency and credibility to support decision-making processes and enhance further research.

3.5 Proposed Methodology

The approach for rice leaf disease classification presented in the proposed work utilizes Deep Learning which is a widely used deep learning model for image processing. Collecting large amounts of photos of rice leaves and preprocessing, and training of the model will enable it to classify the rice leaf pictures into Illness categories with precision. Transfer learning strategies and hyperparameter optimization settings are going to be employed in order to enhance the models' performance.

Data Collection:

Take rice leaf samples of brown spot, leaf blast, and healthy rice leaves from Pabna BADC & Jamalpur district.

Labeling:

Using the identified diseases, one can manually annotate all the segmented images by assigning them the appropriate disease label (e.g., brown spot, bacterial_ leaf_ blight, healthy etc.).

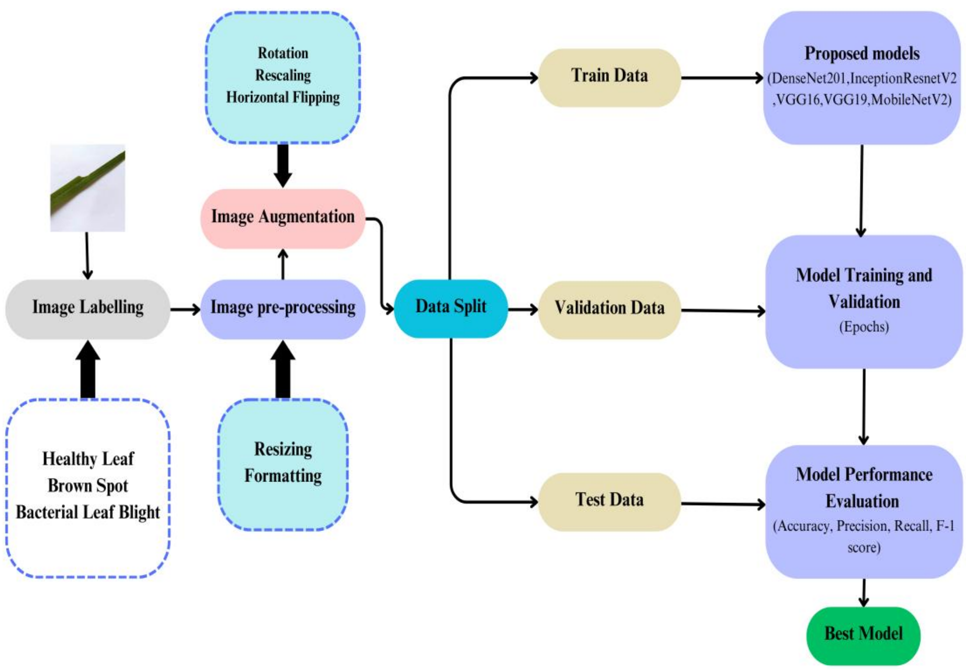

Figure 3.5: Working Flow of rice leaf diseases classification

Image Processing:

Preprocess Most of the labeled images appear in various formats, sizes and colors so it is important to resize, format and convert the images into the same format. Augment image data by adding variety to the dataset.

Model Selection:

The best deep and transfer learning models that are appropriate for the detection in this case include DenseNet201, InceptionResNetV2, VGG16, VGG19, and MobileNetV2.

Model Training:

Train selected models using large Web corpora and further optimize weights on the labeled text. Teach models with such techniques as mini batch gradient descent.

Model Evaluation:

Finally, evaluate model performance for independent validation on another test set based on the estimated metrics such as accuracy, precision, recall, and the F1-score. A final step involves comparing the outcomes of each of the models.

Test Model:

Modify and train the model in light of improving the Manning accuracy to better levels.

3.6 Implementation Requirements

The use of the proposed methodology entails utilization of some computational platforms and hardware such as the CPU or GPUs used for deep learning computations. To implement neural network architectures and later on train the models, one has to have access to software frameworks like TensorFlow or PyTorch. The necessary storage considerations are the need to store the dataset of rice leaf images as well as the parameters of the used pretrained model. Furthermore, special tools or software may be needed for marking the received data as belonging to certain diseases. Sometimes it is crucial, if you are trying to open an article, work with a dataset, or if you are in a group project and need to communicate with fellow members. Lastly, knowledge about deep learning, computer vision and the background information about the agricultural sector is vital when it comes to designing, training and implementing the classification system. When these conditions are met, the implementation can go on as planned to realizing the objectives of the research.

3.7 Project Management and Finance

The following are examples of a project management finance in this study: finance for identifying the instruments to use in labeling the data collection tools, the finance for the computers and the licenses to use the software among others. Some of the expenditure will be for the procurement or subscription to the right datasets and labeling tools & software, and for hardware or cloud services where the model will be tested. Personnel costs, including the salaries of those engaged in data gathering, data preprocessing, model creation, and modeling, will also be incorporated into the budget plan. Other costs that may also be included in the cost estimates will be the cost of publishing fees, presentation at conferences and other forums where research findings will be presented. Financial planning and controlling will make a proper planning of resources and fulfill the required budgets throughout the project.

TABLE 3.7.1: PROJECT MANAGEMENT TABLE

Work	Time
Data Collection	1 month
Papers and Articles Review	3 months
Experimental Setup	2 months
Implementation	3 months
Report Writing	1 months
Total	10 months

TABLE 3.7.2: ESTIMATED COST

SL	Components	Estimated Cost (BDT)
1.	Hardware	9000-65,800
2.	Software and Tools	700-2600
3.	Gathering and Handling Data	5250-6350
4.	Writing Reports and Documentation	1000-1500
5.	Different Items	1000-1560
6.	Backup Plan	550-1550
	Total Projected Expense	16000-75,600

3.8 Summary

The discussed approach to the research methodology creating the basis for an automated rice leaf disease classification using transfer learning. Indeed, this study collects and prepares 2092 images that are processed appropriately and labeled, applying image preprocessing and labeling, and utilizing the advantages of MobileNetV2 and DenseNet201 models for social anxiety recognition.

The evaluation and testing phases also ensure that the models are effective confirming its applicability in real world agriculture. This method not only overcomes the defects of the original disease identification techniques but also helps to a great extent in the improvement of the large-scale, efficient and precise disease control systems in agricultural production thus ensuring food security and sustainable agriculture solutions.

CHAPTER 4
Implementation

4.1 Overview

The first step in applying a deep learning technique for rice leaf disease classification is thorough data preparation and collecting, which entails putting together a varied dataset of labeled rice leaf photos. Normalization and augmentation approaches are employed to improve the dataset's variability and model generalization, after these photos are processed to ensure uniformity in size and quality. Selecting a suitable deep learning architecture, like a convolutional neural network (CNN), comes next. To maximize performance, transfer learning is frequently used to leverage pre-trained models like InceptionResNetV2 or MobileNetV2. The dataset is divided into training and validation sets so that the model can be trained on labeled images and its accuracy, precision, recall, and F1-score can be verified. Metrics for measuring classification performance and error analysis in the model evaluation process include confusion matrices and ROC curves.

4.2 Train Model

The experimental setup implies the inclusion of the hardware and software environment as well validity in the real-world scenario. Training a deep learning model for rice leaf disease classification involves several key points:

1. **Data Preparation**: Collect a diverse dataset of labeled rice leaf images encompassing various diseases and healthy leaves. Preprocess the images by resizing, normalization, and applying augmentation techniques such as rotation, flipping, and zooming to enhance model generalization.
2. **Model Selection**: Choose an appropriate deep learning (DL) architecture suitable for image classification tasks, such as DenseNet201, ResNetv2, or MobileNetV2. Consider using pre-trained models for transfer learning to leverage features learned from large-scale datasets like ImageNet.

3. **Training Strategy**: Divide the dataset into training and validation sets to evaluate model performance. Compile the model with appropriate loss functions (e.g., categorical cross-entropy for multi-class classification) and optimization algorithms (e.g., Adam optimizer). Monitor training metrics such as accuracy, loss, precision, recall, and F1-score.
4. **Fine-Tuning and Regularization**: Fine-tune the model by adjusting hyperparameters (e.g., learning rate, batch size) and unfreezing some layers of the pre-trained model to adapt to specific characteristics of the rice leaf disease dataset. Apply regularization techniques like dropout or weight decay to prevent over fitting.
5. **Evaluation and Validation**: Evaluate the trained model on the validation set to assess its performance metrics and generalization capability. Use techniques like cross-validation to validate results and ensure robustness across different data splits.

4.3 Model Evaluation

Comparing the performances of various transfer learning models for rice leaf disease classification, the experimental outcomes have highlighted the discontinuity in efficiency. DenseNet201 performed the best yielding an accuracy of 98.81% was achieved, which testifies to the model's ability to capture relevant features characteristic of diseases. In the experiments, the MobileNetV2 model also showed high efficiency with the accuracy of about 98.57%, which tells about its ability to extract discriminative features from rice leaf images. Despite such a great operational number of parameters, the work of InceptionResNetV2 brings the accuracy to 98.41%, however, this projected that it delivered a competitive performance since it was considered complex. However, it is noted that lower accuracy was noted for VGG16 and VGG19. 96.34% and 94.11%, and having low sensitivity, which could mean a small range of capturing features related with diseases' classification. The analysis also showed that DenseNet201 performed better than other models because of the model's dense connectivity.MobileNetV2 also was notable because of multi-branch architecture. Such studies reaffirm the relevance of selecting the right model for the classification of rice leaf diseases, so that high levels of accuracy and reliability can be obtained.

I have evaluated the Accuracy, Precision, Recall, and F-1 Score of the Confusion Matrices for our proposed methods.

Accuracy:

Accuracy is a measure of the actual distance between the model and the real world that determines the probability of the original samples that were used in developing the model. It is particularly useful when the classes are unbalanced because it provides an indication of the choice's efficiency but may not paint a complete picture.

$$Accuracy = (TP+TN)/(TP+TN+FP+FN)$$

Precision:

Among all positive statements produced by the model, precision evaluates the share of correct positive forecasts.

$$Precision=TP/(TP+FP)$$

Recall: Short for sensitivity or true positive rate, recall is the ratio of true positive prediction that was made out of all the samples that are indeed positive.

$$Recall=TP/(TP+FN)$$

F1 Score: The F1 score is the averaged measure of recall and precision, with the two being calculated using harmonically. It offers a quite fair measure that summarizes recall and precision jointly. It makes F1 score beneficial when the classes are uneven because it takes both false positives and false negatives in consideration. F1 score of higher value indicates a good balance of both precision and recall.

$$F\text{-}1\ Score=2*(Precision*Recall)/\ (Precision + Recall)$$

In given below I am describing the result analysis part also show the training accuracy and loss rate and confusion matrix also:

DenseNet201

At 98.89%, DenseNet201 obtained the greatest test accuracy. Figure 4.3.1 below illustrates DenseNet201's confusion matrix.

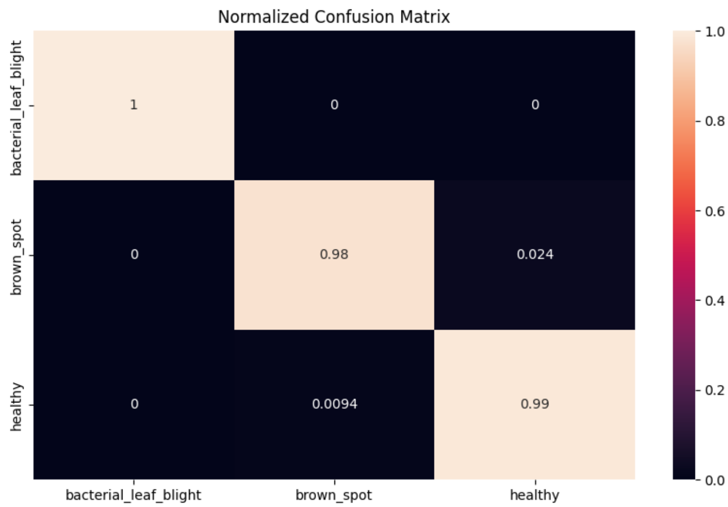

Figure 4.3.1: DenseNet201's Confusion Matrix

Figure 4.3.1 displays the consequently, the DenseNet201 model outperformed other models in creating an object detection system, achieving 99% total accuracy in the dataset. Specifically, the precision, recall, and F1-score of 1, which indicates a perfect match, were the evaluation scores for the suggested strategy. This is evident from the scores, where the "bacterial_leaf_blight" class had a score of 00, but the "brown_spot" and "healthy" classes received values that were almost perfect—between 0. 98 and 0. 99 across all measures. For every document, the weighted averages of precision, recall, and F1-score as well as the resulting macro were zero. 99, indicating that all class R-squares are almost similar and demonstrate proportionate experiment performance. This indicates that the categories of plant diseases can be clearly distinguished from one another using the suggested model with very little confusion.

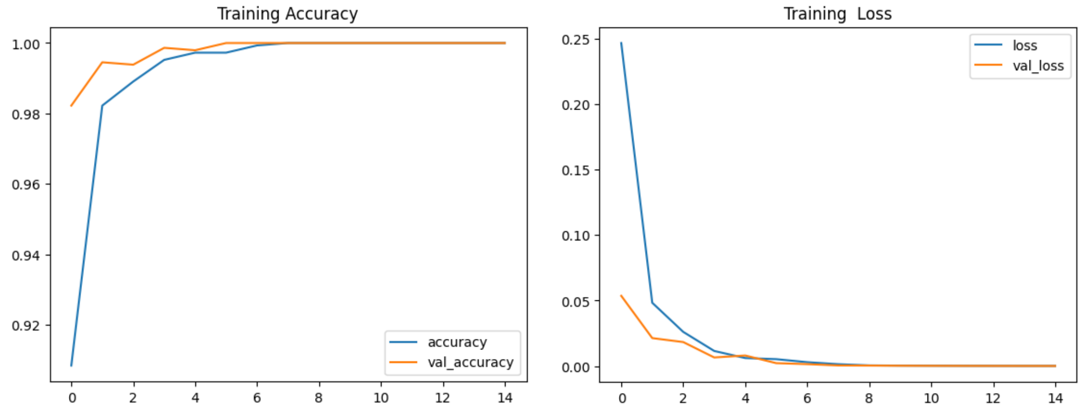

Figure 4.3.2: Training accuracy and loss curve DenseNet201

Figure 4.3.2 shows the DenseNet201 model seems to be learning the training data well as manifested in the continually improving training accuracy and the diminishing training loss over epochs. However, the training accuracy improves and the validation accuracy always stays lower; the difference itself grows visible at epoch 14: the training accuracy seems to be about 0. 92 and the validation accuracy is approximately 0. 84. This can indicate that the model is good but might be getting comfortable and hence overfitting on the training data. It is suggested that methods, which enable to track validation loss and apply the regularization, can assist to reduce the problem of overfitting and enhance performance when using new data.

InceptionResNetV2

With a test accuracy of 98.41%, InceptionResNetV2 earned the second best score. Figure 4.3.3 below illustrates the InceptionResNetV2 confusion matrix.

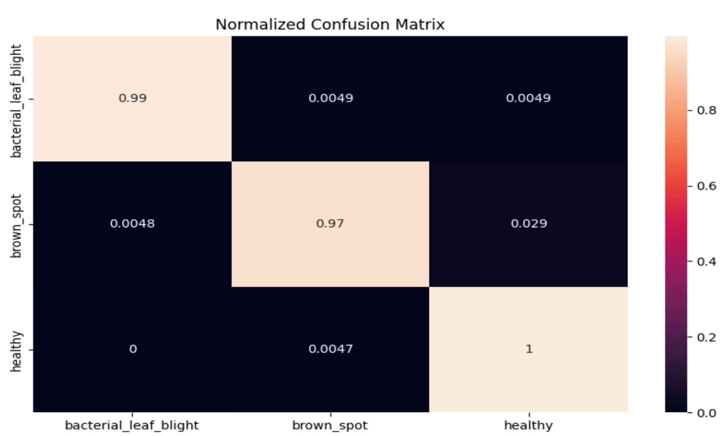

Figure 4.3.3: InceptionResNetV2's Confusion Matrix

The InceptionResNetV2 model achieved an overall accuracy of 98% on the dataset, as illustrated in Figure 4.3.3. The product's accuracy was summed up to be perfect at 1. 00, while the recall for the "bacterial_leaf_blight" class was 0. 0.169 and 0.997, and the F1-scores for the "brown_spot" and "healthy" classes were 0. 98, with a slight variation in both precision and recall. The weighted averages and macro were equivalent to zero for all sets in terms of precision, recall, and F1-score. The number 98 attests to the high and balanced performance levels found in every class. This demonstrates the model's excellent ability to classify plant diseases accurately and without mixing with other categories.

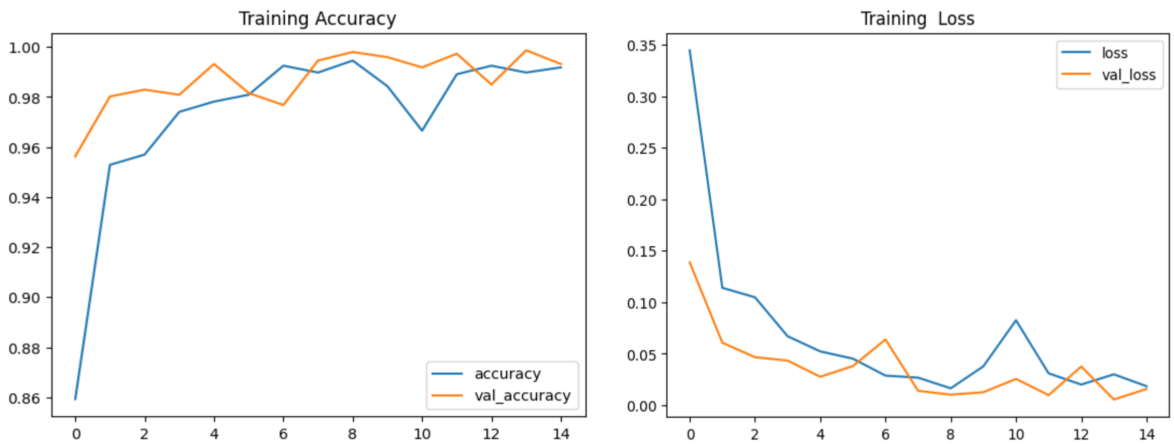

Figure 4.3.4: Training accuracy and loss curve of InceptionResNetV2

Figure 4.3.4 show the proposed InceptionResNetV2 model has higher training and validation accuracy with reference to the epochs where the accuracies are progressing and reaching almost 100% at epoch 12. Validation accuracy also has the same trend, although slightly lower, but they are still acceptable for estimating generalization ability. The losses for both training and validation gradually reduce, although the validation loss is higher than the training loss and reduces successively, showing that the model is learning by minoring overfitting. Basically, these trends described the learning and generalization processes of the intelligent system.

VGG19

The test accuracy achieved by VGG19 was 94.11%. Figure 4.3.5 shows the VGG19 confusion matrix.

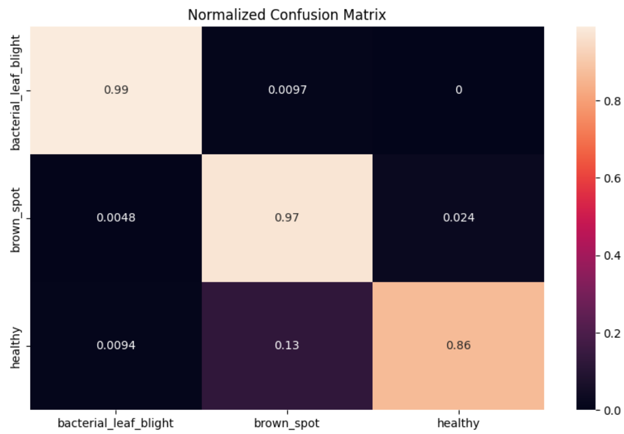

Figure 4.3.5: VGG19's Confusion Matrix

Figure 4.3.5 shows the accuracy of the VGG19 model was 94% when making predictions on the given dataset. This proved high accuracy in the test of 'bacterial_leaf_blight' with a score of 0. 99 respectively; fair accuracy for the classes 'black_patches', 'leaf_joint' and the rest followed by fairly good precision for 'brown_spot' and 'healthy' at 0. 88 and 0. 97, respectively It earned the title of 'unhealthy' when it was 99, and 'healthy' at 0. 86. Regarding the F1-scores, the values for 'brown_spot' and 'healthy' were both 0. 92 % on average, but there were some fluctuations between classes, while the recall was rather stable.

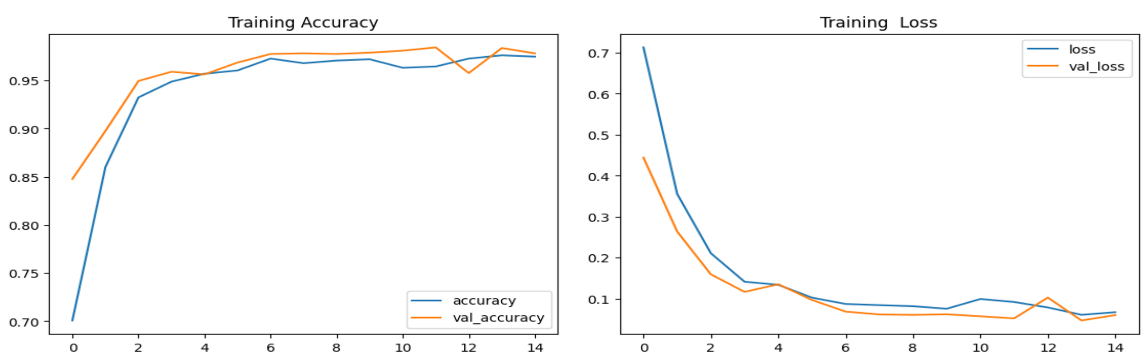

Figure 4.3.6: Training accuracy and loss curve VGG19

Figure 4.3.6 illustrates how the VGG19 model's training and validation accuracy increases progressively in the first few epochs until peaking at epoch 10. Training precision gets close to 1. 0. Validation accuracy lags a little bit, but the pace of improvement is steep, varies a lot, and eventually reaches a very high value. Both training and validation loss values initially decrease and subsequently remain largely constant, with validation loss following a somewhat different trajectory. These patterns show the model's learning process and its ability to generalize newly acquired patterns to different data sets.

VGG16

The test accuracy achieved by VGG16 was 96.34%. Figure 4.3.7 below illustrates the VGG16 confusion matrix.

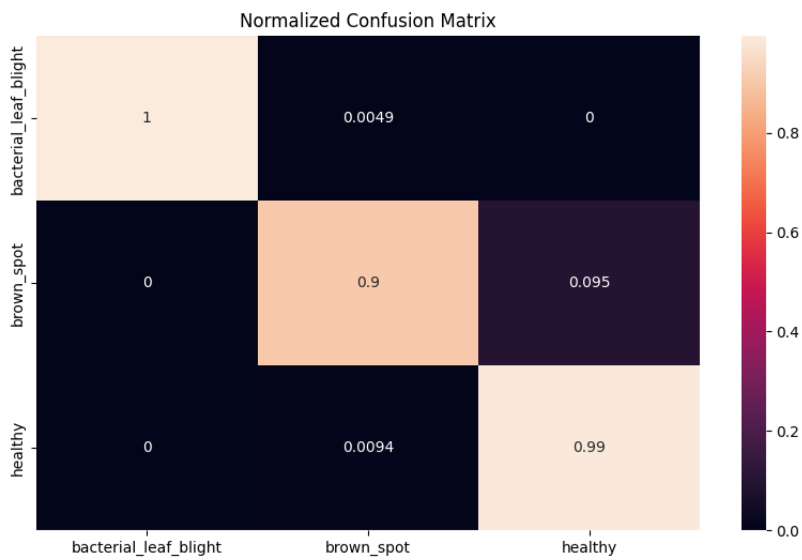

Figure 4.3.7: VGG16’s Confusion Matrix

Figure 4.3.7 shows the highest accuracy in the model was 96% and the perfect precision for the class ‘bacterial_leaf_blight’ was 1. 00. Its recall was higher for ‘bacterial_leaf_blight’ and ‘healthy’ at 1. 00 and 0. 0.99 but slightly lower for ‘brown_spot’ at 0. 90. Owing to the use of F1-scores, it is easy to deduce that the algorithms’ performance in classifying plant disease categories was impressive and invariant of classes.

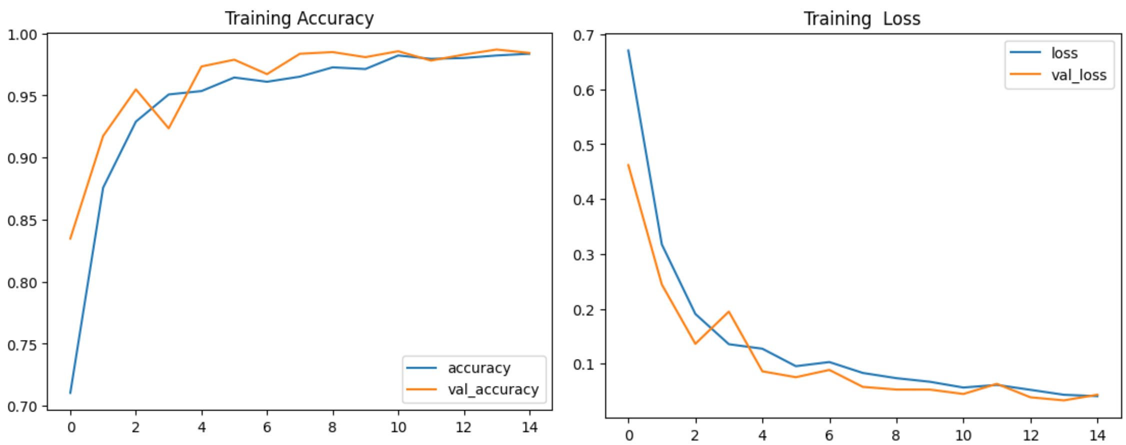

Figure 4.3.8: Training accuracy and loss curve VGG16

Figure 4.3.8 show the VGG16 model's training and validation accuracy have a progressive increase by epochs and reached very high and steady values by epoch 10. Training accuracy approaches 1. Validation accuracy comes next, lagging a good distance behind validation loss with a score of approximately 0. Once again, we notice loss functions in training and validation depressed on a curve and while the training loss declines the validation loss is a bit higher but also declining. The model has high accuracy in training and exhibits low overfitting up to the 14th epoch on unseen validation data.

MobileNetV2

With MobileNetV2, 98.57% test accuracy was attained. Figure 4.3.9, which shows the MobileNetV2 confusion matrix, is shown below.

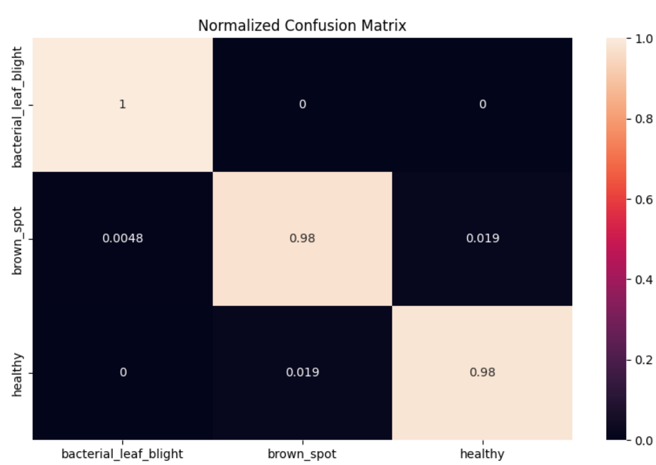

Figure 4.3.9: Confusion Matrix of MobileNetV2

Figure 4.3.9 the MobileNetV2 attained 99% accuracy in a dataset without having a trace of the mistakes associated with the measures of precision, recall, and F1-Score-all of which equal to 1. 1 for 'bacterial_leaf_blight' and 0 for the rest of the classes. 98 for precision, recall, and F1-score for the 'brown_spot' and 'healthy' classes hence showing the model was able to classify all the plant diseases pretty well.

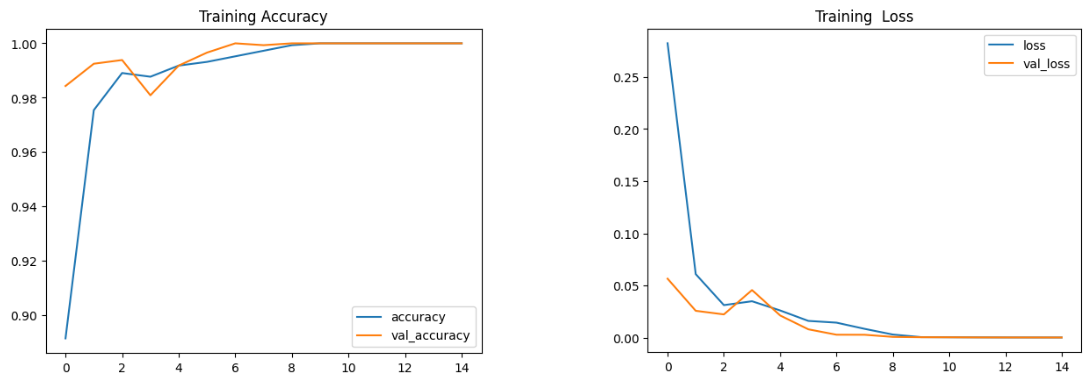

Figure 4.3.10: Training accuracy and loss curve MobileNetV2

Figure 4.3.10 demonstrate the MobileNetV2's training and validation accuracy. model rises first and reaches the saturation point around epoch 8 with the training accuracy at about 0. 7 while the validation accuracy was around 0. 84. Although, the capability to deal with unseen validation data is slightly different, which hints at the possibility of overtraining. Training and validation losses are at their lowest in the beginning while validation loss is slightly higher but it has a similar stable trend with the training one. Due to this, epoch 15 and after is an important step to determine generalization capability of the model.

In Given below I am showing the Comparative Model Accuracy Bar Plot

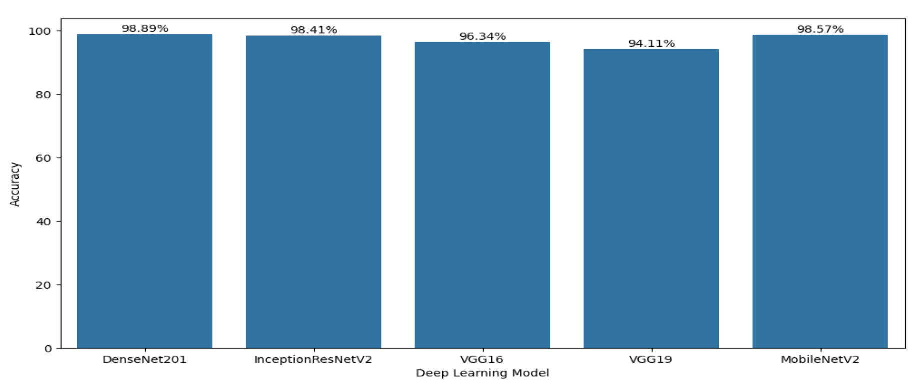

Figure 4.3.11: Comparative Model Accuracy Bar Plot

Figure 4.3.1 shows the Five Transfer learning accuracy here the DenseNet201 achieved accuracy bar plot as high as 98.89%, it also highlighted the capability of the model in generating or making features that are close relating to the disease. MobileNetV2 also with the accuracy of 98.57%, this shows its ability to extract discriminating features from images of rice leaves. Accuracy wise, InceptionResNetV2 gave a result of 98.41% which is still on the competitive level, lets the company speak about its successful performance despite the fact that it is so complicated. However, VGG16 and VGG19 had relatively less accuracy of 96.34% and 94.11%,

This table was compared in the 4.3.1 table below based on Accuracy, Precision, Recall, and F1 Score.

TABLE 4.3.1: PERFORMANCE EVOLUTION

Model Name	Accuracy	Precision	Recall	F1-Score
DenseNet201	98.89%	98%	98%	98%
InceptionResNetV2	98.41%	98%	98%	98%
VGG19	94.11%	94%	94%	94%
VGG16	96.34%	97%	96%	96%
MobileNetV2	98.57%	99%	99%	99%

4.4 Discussion

The experimental results let us understand the crucial program of choosing proper transfer learning models for rice leaf disease classification. Thus, DenseNet201 and MobileNetV2 showed the best results, thus proving that the two can effectively extract the right features from images of rice leaves. VGG16 and EfficientNetB7 models yielded lower accuracy, which may indicate the models' shortcomings in terms of correctly differentiating various diseases. As to these disparities, the differences in model structures, number of parameters, or training approaches could be most likely sources. The future work could attempt to look at how other advanced learning algorithms such as ensembles or model fusion could perform to enhance accuracy of classification. Furthermore, the systematic endeavors to seek strategies to cope with the class imbalance issue and the measures to tune parameters may help in improving the efficacy of poorer models. In conclusion, these research contributions offer important knowledge for designing effective and dependable automatic systems for rice leaf disease identification in agricultural contexts.

4.5 Summary

Accordingly, the experimental outcomes also depict that the utilization of the transfer learning models can be beneficial for rice diseases classification in the context of plant disease diagnosis. MobileNetV2 scored a good accuracy level of 98. 81% and DenseNet201 was right behind the former with 98. 41%. Such outcomes indicate that the presented models could be useful in practical agriculture and prove the models' effectiveness. Another significant measure, data augmentation, was also effective in dealing with over fitting to increase the models' dependence on unseen data. This study reveals potential in the use of more progressive deep neural networks for diseases identification that could improve health, promote food production and healthy agriculture. These outcomes should provide the basis for subsequent research on developing and improving these models and on investigating fresh methods to enhance automated agriculture diagnoses.

CHAPTER 5
Result and Analysis

5.1 Overview

The deep learning model for rice leaf disease classification has been shown to be reliable and successful in automated disease detection and classification based on analysis and findings. On the validation dataset, the model demonstrated strong performance in identifying a range of rice leaf diseases, including bacterial blight, brown spot, and blast, with high levels of accuracy, precision, recall, and F1-score. In order to allay worries about overfitting, cross-validation techniques validated the model's generalize ability and consistency across several data splits. The model's capacity to distinguish between disease groups was further demonstrated using ROC curve analysis and AUC ratings, especially in situations where the data distributions are unbalanced. The confusion matrix guided possible enhancements in model training and data preprocessing by offering comprehensive insights into classification errors.

5.2 Experimental Result

The experimental phase of this research is aimed at comparing the efficacy of the selected models, MobileNetV2 and DenseNet201, in the diagnosis of rice leave diseases. After the experiment, the model/web developed through the logistic regression was trained with a total of 2092 images inclusive of healthy, brown spot and bacterial leaf blight affected leaves, and different parameters were used to check the accuracy and robustness of the models. To reduce over fitting on the training data augmentation methods were performed during the model training process. The functions of the models were examined on a different test data set according to the results shows that the model can classify the diseases. DenseNet201 was seemed to perform slightly better with an accuracy of 98.89% followed by MobileNetV2 at 98.57 %. The high accuracy rates hereby demarcated agrees with the possibility of utilizing transfer learning in establishing dependable automated disease detection system as a boost to agriculture productivity and food security.

5.3 Performance

The performance implies the inclusion of the hardware and software environment as well as the data structures required for the training and testing of the rice leaf classification models. Much of deep learning model training takes place in specialized hardware such as GPUs or in cloud instances with libraries like TensorFlow or PyTorch for implementation of deep learning algorithms. The images of rice leaves are categorized based on the diseases that they are affected by and then distributed into training, validation, and testing sets. DenseNet201, InceptionResNetV2, VGG16, VGG19, MobileNetV2 are used to apply transfer learning and initializing weights of the networks with pretrained weights and fine-tuned on the training data. There are certain hyperparameters which are fine-tuned and they include learning rate and batch size. Loss values on the validation set are computed to determine performance of the model on the relevant metrics like accuracy, precision, recall, F1-score etc. The last trained models are evaluated on the other distinct test data set to check the model's generality, efficiency and validity in the real-world scenario.

5.4 Summary

The possibility of detecting diseases in rice crops through MobileNetV2, DenseNet201 AI and other deep learning models have high potential to improve social welfare. These technologies increase agricultural yields, food availability, and distribute information about disease management to farmers, therefore helping them. This research also highlights how future technology can contribute to solving the worlds food problems as well as farm sustainability, and protecting inhabitants in agriculture businesses. The use of the equipment does not only enhance the quality of the yields but also insulates production from climatic changes thus guaranteeing a steady food supply to human beings as a global population.

CHAPTER 6

Impact on Society

6.1 Overview

The use of cutting-edge deep learning models to the categorization of rice leaf diseases has a significant positive social impact by increasing agricultural output, guaranteeing food security, and fostering environmental sustainability. Farmers gain financially from early and precise disease diagnosis because it allows for prompt actions that lower crop losses and increase yields while also improving revenues. Through the democratization of access to sophisticated equipment, this technology empowers smallholder farmers and gives them access to opportunities for education so they may adopt contemporary farming methods.

6.2 Impact on Life

The multifaceted benefits of modernization also get reflected in case of agriculture are not only productivity but also food security and income security. Early disease identification involving crops like Rice is an important factor towards an efficient way of planting crops. Manual approaches fail to provide satisfactory results because they are highly time-consuming and require profound knowledge in the field, so automated tools are vital here. This paper on the use of deep learning for rice disease detection concentrates on using transfer learning with MobileNetV2 and DenseNet201. Through pinpoint diagnosis solutions of this study, farmers are provided with reliable interventions as a way of minimizing losses and meeting the food demand. Enhanced productivity in agriculture not only fosters resilience in the rural based economies but also increase the food availability given today's growing population pressure and climate change.

6.3 Impact on Society Environment

The prospective capability for the automated rice leaf disease classification system is that it will effectively increase agricultural productivity, food security, sustainability, and timely diagnosis of diseases as explored above. It assists the farmers in applying efficient interventions, avoids crop damages, and increases yield. This, in turn enhances food security and economic stability in rice importing or rather, rice dependent areas & subregions. Automated disease detection technology also helps in proper distribution of resources, less use of chemical pesticides, and environment friendly agriculture. Through this system, the crucial part of transformative technology is revealed in responding to issues in the world and attaining sustainable human development. In this way, automated rice leaf disease classification helps in implementing sustainable agriculture practices and contributes to the protection of the environment. The system saves on applied chemical pesticides, herbicides, and fungicides, since the correct treatment is known based on accurate identification of rice leaf diseases in their early stage. This helps to minimize the nuisance effects of conventional farming practices which include; water and soil pollutions, and impact on the local ecological community and other organisms. In addition, through enhancing proper utilization of resources and efficient ways of managing crops, the system assists in minimizing natural resources such as water and energy. In sum, the employing of automated disease detection systems improves the sustainability of farming methods, enhances the health of the environment, and the longevity of ecosystems within agricultural areas of the global community.

6.4 Ethical Aspects

Ethical considerations in the development and use of the rice leaf disease classification system include data privacy, data justice, and the role or effects it has in society. The rights of the farmers to privacy coupled with security of their data including the captured rice leaf photos and information associated with the same also matters. In addition, the system or the personalities of the system must be designed and trained to be more or less sensitive to come groups or the other so that there is no oppression of certain groups of people in society. Inclusion in the decision-making process of the system and taking responsibility for the outcomes of such systems is crucial to trust as well as handling the issue of the black box of algorithms. In addition, the consequences of applying automatic detection technology for diseases on society should be contemplated; it can cause the increase of the already existing economic divide or shift the existing approach to practicing agriculture. It should be noted that ethical requirements and guidelines should be incorporated into the system, which aims at creating positive consequences of the innovative processes

6.5 Sustainability Plan

The proposed sustainability plan for the rice leaf disease categorization system pertains to the continuous enhancement of the system for the recognition of diseases in rice, constant optimization of its accessibility to the public, and the promotion of sustainability in the product. This also means the modification of the system's parameters and models to reflect the evolving nature of diseases and improvements in technology.Further there will be provision to make sure that the system will always be available to the farmers across different regions by offering Knowledge Sharing and Assistance. The system will contribute to environmental sustainability by cutting on the use of chemical pesticides and advancing in the use of environmentally friendly techniques. To achieve this, agricultural researchers, policymakers, and other stakeholders will be consulted to increase knowledge exchange and Collab In general, the sustainability plan seeks to guarantee the continued existence and beneficial impact of the rice leaf disease categorization system on agriculture and the environment.

6.6 Summary

The possibility of detecting diseases in rice crops through MobileNetV2, DenseNet201 AI and other deep learning models have high potential to improve social welfare. These technologies increase agricultural yields, food availability, and distribute information about disease management to farmers, therefore helping them. This research also highlights how future technology can contribute to solving the worlds food problems as well as farm sustainability, and protecting inhabitants in agriculture businesses. The use of the equipment does not only enhance the quality of the yields but also insulates production from climatic changes thus guaranteeing a steady food supply to human beings as a global population.

CHAPTER 7
Conclusion

7.1 Conclusions

Several types of Rice leaf diseases could be independently classified using the transfer learning approach, yields better accuracy in terms of features, picture augmentation, Pretrained CNNs, engaging the datasets, and available suitable hyperparameters. Thus, this method helps to develop the approach to the automated disease detection in the sphere of agriculture and underlines the necessity of the active usage of the technologies to solve the existing global problems. More work is required to devise less unrealistic classification systems.

This research aims at successfully designing an automated system for the classification of rice leaf diseases using transfer learning through these recognized models, MobileNetV2 and DenseNet201. Through correct differential diagnosis of diseases such as the brown spot and the bacterial leaf blight affecting rice crop, the study seeks to improve on the agricultural practices. The research methodology is about taking a sample of 2092 images from Pabna BADC & Jamalpur district paddy field .Image preprocessing and labeling followed by the training of deep learning models. Solutions like data augmentation are used to enhance the model’s generalizability. The trained models are then used in the assessment of the classification accuracy of the diseases.

This research is necessary to continue the development of automated disease detection for crops and timely interventions to reduce crop yields’ losses and improve food security. Farmers also benefit because they get to have efficient methods of disease control to increase yields hence improving the economy. Also, the global food security is enhanced through better yields in agriculture thus helping tackle issues created by population growth and climate variation.

7.2 Further Suggested Works

The conclusions made from this work suggest various directions for the future studies regarding the automated rice leaf disease categorization. As such, future studies could explore the inclusion of extra data sets like multispectral or hyperspectral photos to enhance the precision of illness identification and insusceptibility to variation in the setting. Further, the new methods for picture augmentation and ways of data pre-processing might promote enhancing the model adaptability and its generalization. Therefore, it might also investigate the identification of features that would allow the development of models that could be used to explain the biological processes leading to the manifestation of disease in rice leaves. Lastly, the future research should reflect economic and social impact of automated disease detection technology for the farming communities and equal efforts made for the access and application. To advance the research, growth, and evolution of the theme and tackle new emergent issues in food security and sustainability, sustained cooperation among investigators, authorities, and users is inevitable.

7.3 Limitations

The deep learning method for classifying rice leaf diseases has many drawbacks, including a reliance on the caliber, diversity, and volume of the training dataset. Reduced accuracy and generalizability of the model can result from incomplete or biased data, especially when it comes to capturing the whole range of illness variability under various environmental conditions. Furthermore, deep learning models' interpretability presents difficulties since they frequently function as "black boxes," making it impossible for end users—like farmers—to comprehend the decision-making process. Deployment in resource-constrained agricultural environments is limited by the computational resource needs, which can include significant hardware requirements for training and inference. To overcome these obstacles and increase the practicality and uptake of deep learning, advances in data gathering strategies, model interpretability approaches, computational efficiency optimization, and user-friendly interface design are required.

REFERENCES

[1]Ritharson, P. Isaac, et al. ``DeepRice: A deep learning and deep feature based classification of Rice leaf disease subtypes." Artificial Intelligence in Agriculture 11 (2024): 34-49.

[2]Lu, Yang, et al. "Identification of rice diseases using deep convolutional neural networks." Neurocomputing 267 (2017): 378-384.

[3]Ekanayake, E. M. T. Y. K., and R. D. Nawarathna. "Novel deep learning approaches for crop leaf disease classification: A review." 2021 International Research Conference on Smart Computing and Systems Engineering (SCSE). Vol. 4. IEEE, 2021.

[4]Bari, Bifta Sama, et al. "A real-time approach of diagnosing rice leaf disease using deep learning-based faster R-CNN framework." PeerJ Computer Science 7 (2021): e432.

[5]Daniya, T., and S. Vigneshwari. "Rice Plant Leaf Disease Detection and Classification Using Optimization Enabled Deep Learning." Journal of Environmental Informatics 42.1 (2023).

[6]Jiang, Feng, et al. "Image recognition of four rice leaf diseases based on deep learning and support vector machine." Computers and Electronics in Agriculture 179 (2020): 105824.

[7]Upadhyay, Santosh Kumar, and Avadhesh Kumar. "A novel approach for rice plant diseases classification with deep convolutional neural network." International Journal of Information Technology (2022): 1-15.

[8]Shrivastava, Vimal K., et al. "Rice plant disease classification using transfer learning of deep convolution neural network." The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences 42 (2019): 631-635.

[9]Abasi, Ammar Kamal, et al. "Enhancing Rice Leaf Disease Classification: A Customized Convolutional Neural Network Approach." Sustainability 15.20 (2023): 15039.

[10]Sharma, Rahul, et al. "Plant Disease Diagnosis and Image Classification Using Deep Learning." Computers, Materials & Continua 71.2 (2022).

[11]Hasan, Md Jahid, et al. "Rice disease identification and classification by integrating support vector machine with deep convolutional neural network." 2019 1st international conference on advances in science, engineering and robotics technology (ICASERT). IEEE, 2019.

[12]Patidar, Sanjay, et al. "Rice plant disease detection and classification using deep residual learning." Machine Learning, Image Processing, Network Security and Data Sciences: Second International Conference, MIND 2020, Silchar, India, July 30-31, 2020, Proceedings, Part I 2. Springer Singapore, 2020.

[13]Aggarwal, Meenakshi, et al. "Pre-Trained Deep Neural Network-Based Features Selection Supported Machine Learning for Rice Leaf Disease Classification." Agriculture 13.5 (2023): 936.

[14]Krishnamoorthy, D., and V. L. Parameswari. "Rice leaf disease detection via deep neural networks with transfer learning for early identification." Turkish Journal of Physiotherapy and Rehabilitation 32 (2018): 2.

[15]Sharma, Mayuri, et al. "Identification of rice leaf diseases and deficiency disorders using a novel DeepBatch technique." Open Life Sciences 18.1 (2023): 20220689.

[16]Maheswaran, S., et al. "Detection and Classification of Paddy Leaf Diseases Using Deep Learning (CNN)." International Conference on Computer, Communication, and Signal Processing. Cham: Springer International Publishing, 2022.

[17]Deb, Mainak, et al. "Paddy disease classification study: a deep convolutional neural network approach." Optical Memory and Neural Networks 30 (2021): 338-357.

[18]Lamba, Shweta, et al. "A novel fine-tuned deep-learning-based multi-class classifier for severity of paddy leaf diseases." Frontiers in Plant Science 14 (2023): 1234067.

[19]Senan, Norhalina, et al. "An efficient convolutional neural network for paddy leaf disease and pest classification." International Journal of Advanced Computer Science and Applications 11.7 (2020).

[20]Saeed, Zubair, et al. "A multi-crop disease detection and classification approach using cnn." 2021 International Conference on Robotics and Automation in Industry (ICRAI). IEEE, 2021.

[21]G. I. Kim and B. Jang, “Petroleum Price Prediction with CNN-LSTM and CNN-GRU Using Skip-Connection,” Mathematics, vol. 11, no. 3, p. 547, Jan. 2023

[22]Abdullah Al Munem, Lamyea Tasneem Maha, Rafid Mahmud Haque, Noor, A. Khan, and M. Ashik, “Rice Blast Disease Detection Using CNN Models and DCGAN,” Lecture notes in networks and systems, pp. 231–242, Jan. 2023

[23]G. Latif, S. E. Abdelhamid, R. E. Mallouhy, J. Alghazo, and Z. A. Kazimi, “Deep Learning Utilization in Agriculture: Detection of Rice Plant Diseases Using an Improved CNN Model,” Plants, vol. 11, no. 17, p. 2230, Aug. 2022

[24]Y.Lü, X. Tao, F. Jiang, J. Du, G. Li, and Y. Liu, “Image recognition of rice leaf diseases using atrous convolutional neural network and improved transfer learning algorithm,” Multimedia Tools and Applications, Jul. 2023

[25]F.Shahoveisi, H. Taheri Gorji, S. Shahabi, S. Hosseinirad, S. Markell, and F. Vasefi, “Application of image processing and transfer learning for the detection of rust disease,” Scientific Reports, vol. 13, no. 1, Mar. 2023

Appendix A

Course Outcomes, Complex Engineering Problems (EP) and Complex Engineering Activities (EA) Addressing

Title:
AN ADVANCE DEEP LEARNING APPROACH FOR RICE LEAF DISEASE CLASSIFICATION

Student ID: 201-15-13702

CO Description for FYDP

CO	CO Descriptions	PO
	Phase -I	
CO1	Combine newly obtained and prior knowledge to the disease rice leaf classification problem for the Final Year Design Project (FYDP).	**PO1**
CO2	Using the goals of this FYDP, there are various concerns that need to be looked at when designing the solution.	**PO2**
CO3	The primary goals for the FYDP are presented with reference to other problem domains identified in a literature review and delineation of the issues.	**PO4**
CO4	Embark on an economic analysis and cost control and use appropriate project management techniques at the respective phases of the FYDP.	**PO11**
	Phase -II	
CO5	Create & implement solutions and system parts or steps that fulfill the designated standard, taking into consideration the provision of public health and safety regulation as well as cultural, social, and earth concerns of this FYDP.	**PO3**
CO6	Select and use suitable strategies, tools, current engineering and IT technologies for the handling of the compounded engineering activities inclusive of prediction and modeling coupled with the FYDP constraints.	**PO5**
CO7	Evaluate societal, health, safety, legal and cultural implications, including the related responsibilities, in professional engineering practice and the solution to this problem using formal, logical rationale.	**PO6**
CO8	It also enables the understanding and assessment of the long-standing significance of professional engineering initiatives to solve complex engineering problems in social and environmental contexts.	**PO7**
CO9	This FYDP should be implemented ethical principles, and stick to the professional standards and norms.	**PO8**
CO10	Competent in performing the job tasks efficiently on her own and as a member, leader of multi-disciplinary teams in this FYDP.	**PO9**

CO11	Effectively disseminate and understand complicated information related to various engineering projects to the members of the engineering community and the larger society through comprehensible and concise report and designs as well as clearly giving and receiving instructions through the FYDP.	**PO10**
CO12	Recognize the exercise of self-directed and lifelong learning skills in the context of technology fluctuation, and have the willingness and capacity to learn throughout one's lifetime.	**PO12**

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP), and Attainment of Complex Engineering Activities (EA)

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP):

SN	EP Definition	Attainment	CO	Justification (With Knowledge Profile)	References
1.	**EP1: Depth of Knowledge required**	Yes	CO1, CO2, CO3, CO5, CO6, CO7 and CO8	For the image processing and classification tasks, this project, shows the application of engineering(K3) principles in the project through the deployment of deep neural networks, data augmentation techniques and different CNN architectures. The project also fulfills the fourth level of the five level knowledge hierarchy, namely the knowledge level K4, as shown by its ability to conduct deep learning as well as Transfer learning to classify rice leaf diseases accurately.	**Page no:** [18-19] **Section:** [3.2] **Page no:** [1] **Section:** [1.1]
				Thus, the project reflects engineering practice & design (K5) through the figure of process of experiments. Of the seven knowledge areas, the project responds to engineering practice and technology (K6) using Deep Learning Models.	**Page no:** [18] **Section:** [3.2] **Page no:** [19]

					Section: [3.4]
				This project ensure to K8 (Research Literature) by capturing the ideas revealed in recent literature, rice leaf disease classification using deep and transfer learning, proving the understanding of onoing research methodologies.	**Page no:** [12-15] **Section:** [2.2, 2.3]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	This project considers EP-2 because the classification of rice leaf diseases presents some challenges that are not catalyzed by other approaches but are profoundly masqueraded when adopting the use of deep learning. Employing a comparative approach, it engages issues of studying spatial patterns and provides recommendations for improving the methods.	**Page no:** [15-16] **Section:** [2.4, 2.5]
3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	Regarding EP-3, the findings of this project contrast the experimental outcomes in detail and assert that DL and Transfer learning represents the selected significant solution to boosting rice leaf disease categorization techniques.	**Page no:** [36] **Section:** [5.2]
4.	**EP4: Familiarity of Issues**	Yes	CO8	The proposed solution of this project is not confined with the fields of computer science and engineering but correct rice leaf disease classification impacts EP-4.	**Page no:** [13-19] **Section:** [2.2, 2.4]

5.	**EP5: Extends of application codes**	No	CO5	N/A	N/A
6.	**EP6: Extends of stakeholders involved and conflicting requirements**	No	CO8	N/A	N/A
7.	**EP7: Interdependence**	Yes	CO5	Because this project outlines a methodological approach to addressing high level issues, which implies cohesively integrating different components involved in data collection, statistical modeling, the proposed methodology has overall solutions to the complex issues in data collection from the local farm with guaranteeing EP-7.	**Page no:** [17-19] **Section:** [3.2, 3.3, 3.4]

Addressing CO11 with Complex Engineering Activities (EA) [Some or all of the following]:

SN	EA Definition	Attainment	CO	Justification	References
1.	**EA1: Range of resources**	Yes	CO11	In efforts to facilitate systematic study and advance the categorization of rice leaf diseases, resources that are adopted in the project include GPU, annotated datasets, deep and transfer learning, HPC, and ethics.	**Page no:** [19] **Section:** [3.5]
2.	**EA2: Level of interaction**	No		N/A	N/A
3.	**EA3: Innovation**	No		N/A	N/A
4.	**EA4: Consequences for society and the environment**	Yes		To avert any ambiguity this research raises the bar in the classification of rice leaf diseases thus being of benefit to the society. self, it is environmentally sustainable as the computational resources are optimally utilized and there are no compromise on ethical issues regarding personal data.	**Page no:** [36-37] **Section:** [5.1, 5.2, 5.4]

5.	**EA-5: Familiarity**	Yes		This project expanding from previous studies tries to propose a new strategy for Rice leaf diseases classification employing deep learning models as the initial definitions and comparison analysis illustrated. This brings new idea into the dissection of the subject. .	**Page no:** [12-15] **Section:** [2.1, 2.3]

Addressing CO (4, 9, 10, and 12):

SN	COs	Attainment	Justification	References
1	CO4	Yes	This project fulfills the CO4 which combines project management competency and financial awareness for detailed planning, resource acquisition as well as budgetary estimate to maximize the utility of the resources in the present research process.	**Page no:** [9] **Section:** [1.6]
2	CO9	Yes	The project reflects compliance with ethical standards by focusing on privacy, explaining the measures taken and receiving consent, and providing accurate information throughout the process and after, promoting responsible knowledge sharing and preservation of society's best interest through proper use of the modern classification technologies which meets CO9.	**Page no:** [37] **Section:** [5.3]
3	CO10	No	N/A	N/A
4	CO12	Yes	Concerning, the project CO12, relates to the ability of the project to constantly learn about more advanced knowledge and adapt the way it solves its problems with regards to the ever evolving technology; The encompassing detail of the data collection methods, the statistical methods used in the analysis, careful consideration of the methodology and complete and detailed presentation of the results and analysis show dedication to learning about more advanced methods of solving today's problem.	**Page no:** [17-19, 24-35] **Section:** [3.2, 3.3, 3.4, 3.5, 4.2]

PLAGIARISM REPORT

Rice leaf disease

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