CLASSIFICATION OF RICE LEAF DISEASE THROUGH IMAGE ANALAYSIS AND DEEP

Learning.

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 **"Classification of Rice Leaf Disease Through Image Analysis and Deep"**, submitted by **Md. Nazmus Shakib, ID No: 191-15-12100** 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 July, 2024.

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DECLARATION

I hereby declare that, this project has been done by me under the supervision of **Dr. Zahid Hasan, Assistant professor, Department of CSE,** Daffodil International University. I also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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ABSTRACT

This work presents a comprehensive deep learning method for precise and effective disease prediction of rice leaves. With Convolutional Neural Networks (CNN), I developed a model that outperforms conventional methods for diagnosing illnesses of rice leaves. Images of both healthy and injured rice leaves were added to the dataset after thorough preprocessing to guarantee model robustness. Appropriate hyperparameters found by an ablation study led to the successful deployment of a CNN model. My model achieves 98.35% training accuracy and 95.38% and 95.22%, respectively, sensitivity and precision rates. The model was able to distinguish healthy leaves with reliability as seen by the high Specificity and Negative Predictive Value (NPV) and low False Positive Rates (FPR). Predictive dependability of the model is shown by the Matthews Correlation Coefficient (MCC) of 94.67%, and precision-recall balance by an F1 score of 95.20%. Because accurate and early disease identification can significantly affect crop yield and food security, this research has broad societal implications. Environmentally speaking, the strategy promotes environmentally friendly farming methods by enabling focused actions that can lower pesticide use. Ethically speaking, the study addresses data privacy and equal access to technology. Future study is discussed on the possible extension of the model to other crops and its connection with Internet of Things devices for real-time monitoring. This work not only progresses agricultural AI but also sets the standard for next studies on environmentally friendly farming methods.

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CHAPTER 1

Introduction

1.1 Introduction

The field of precision agriculture has been revolutionized in terms of managing crop health and maximizing yields, thanks to the rapid advancements in artificial intelligence technology. In the center of this agricultural revolution is the use of machine learning models to identify and classify diseases in staple crops like rice. For many people worldwide, rice is a staple diet, so it is essential to food security [1]. But a number of diseases can seriously reduce its output and quality. The accompanying flowchart shows a whole strategy for resolving this problem by using severity-based classification of rice diseases [2].

This approach uses the strengths of convolutional neural networks (CNNs), a kind of deep learning algorithm that is particularly good at handling visual data. All of it begins with careful dataset preparation to guarantee representation and quality of the data [3]. After this basic stage, the dataset is manipulated via data augmentation methods to artificially increase the model's generalization from a range of disease patterns and presentations [4]. The approach makes sure the model is assessed properly by dividing the dataset into training and testing parts [5]. Then a variety of sophisticated CNN architectures are applied, such as a proprietary CNN with soft attention methods and Mobile Net and VGG variants. Accuracy and effectiveness of these models in picture categorization tasks are well established.

One of the main features of the approach is the iterative process of hyperparameter tuning, which enables the parameters of the model to be changed to achieve best performance [6]. The proposed robust model, which is supposed to be more accurate and dependable in determining the severity of rice diseases, depends on this fine-tuning [8].

With the creation of this approach, agricultural technology underwent a sea change and farmers, agronomists, and researchers now had a trustworthy instrument. It is a prime illustration of how artificial intelligence might revolutionize current practices and steer the agricultural industry toward a time when decisions are made scientifically and data-driven.

1.2 Motivation

The importance of rice in global food security motivated the development of such comprehensive rice disease classification technology [7]. It is grown all throughout the world and is the primary source of nutrition for billions of people. Disease outbreaks in rice harvests can cause massive losses, damaging economies and people. Traditional disease identification approaches, which frequently rely on human expertise, are time-consuming and prone to human mistake [9].

The technological motivation for this discovery is also intriguing. Machine learning, particularly deep learning, has progressed to the point that its application in agriculture can result in major gains [6]. The goal is to use these technological advances to build a system that is not only accurate but also scalable and accessible.

The methodology addresses the need for early identification and intervention, which can significantly reduce the effect of diseases, by proposing a model that can correctly categorize disease severity. It is also a step toward democratizing agricultural expertise, reducing reliance on scarce human experts, and providing farmers with actionable insights.

1.3 Rationale of the Study

This study has two goals: to improve agricultural productivity and to advance the use of machine learning in agriculture. The study is based on the belief that prompt and precise disease classification can lead to better disease management tactics, resulting in increased agricultural yield and quality. Furthermore, it investigates the frontier of bringing cutting-edge machine learning models to a domain where they have the ability to make a concrete impact, paving the way for future precision agriculture research and application.

1.4 Research Questions

1. How can machine learning models be improved to correctly diagnose the severity of rice diseases based on picture data?
2. What is the relative efficacy of various CNN designs in disease severity categorization in rice crops?

1.5 Expected Output

The research is supposed to have the following results:

1. Development of a strong machine learning model that may correctly classify diseases of rice.
2. A large collection of enhanced and preprocessed rice disease images, prepared for use in next research.
3. An evaluation of many CNN architectures to show how well suited they are for uses in agricultural image categorization.
4. A paradigm for illness categorization hyperparameter optimization.
5. Empirical findings in favor of AI application in precision agriculture, which may result in better crop management and increased outputs.

1.6 Project Management and Finance

The research work doesn’t get fund from any individuals or organization.

1.7 Report Layout

In Chapter 1, the introduction, objectives, and key research inquiries of the study are outlined. In Chapter 2, concise synopses of the literature review are provided. In Chapter 3, the proposed methodology is described in detail. In Chapter 4, the experimental outcomes of the paper are described and examined. The fifth chapter discusses the sustainability plan, societal and environmental impacts, and ethical considerations. The sixth chapter concludes the present investigation and outlines a strategy for subsequent endeavors.

CHAPTER 2

Background

2.1 Preliminaries/Terminologies

Recent advancements in agricultural technology have led to the development of state-of-the-art systems for the detection and classification of rice plant diseases. Various studies have focused on utilizing image processing techniques to categorize and identify different types of diseases affecting rice leaves. The use of image segmentation and machine learning algorithms has been instrumental in achieving accurate classification of rice leaf diseases, with a focus on features such as color, texture, and shape. These advancements have significantly contributed to the field of agricultural disease prediction and have the potential to revolutionize farming practices.

2.2 Related works

In [14], the detection and categorization of rice plant illnesses were accomplished using image processing and machine learning approaches. The authors employed K-means clustering to separate the sick area of the rice leaves, then utilized Support Vector Machine (SVM) for classification. They attained an ultimate accuracy of 93.33% and 73.33% on the training and test datasets, respectively. Our work utilized the same dataset, however, our methodology yielded superior accuracy for both the training and test datasets. In their study, Majid et al. [1] created a smartphone application specifically designed for identifying diseases in paddy leaves. In this study, the researchers utilized the Probabilistic Neural Network (PNN) classifier with fuzzy entropy. This study employed fuzzy entropy as a method to extract paddy leaf diseases, and a Laplacian filter was utilized to enhance the image. In their study, Rathore and Prasad (2) introduced a deep learning system for automatically detecting rice leaves. They employed a Convolutional Neural Network (CNN) architecture for the purpose of picture classification. In a study conducted by Matin et al. [3], the AlexNet technique was utilized to detect three common rice leaf diseases. The study achieved a surprising outcome of 99% accuracy. The training data consisted of 70% of the dataset, while the remaining 30% was used for testing. Sladojevic et al. (2016) devised a plant disease detection model utilizing Convolutional Neural Networks (CNN)

[4]. This model has the capability to accurately identify and classify 13 distinct forms of plant diseases. They achieved more precision with this model. In their study, the scientists proposed a method for identifying three prevalent forms of illnesses affecting rice leaves. The backdrop of the afflicted image is removed by applying a saturation threshold, and the impacted part is segmented using a hue threshold. In this study, the photos are analyzed to extract several characteristics, including color, form, and texture, which are then utilized as a feature vector. XGBoost is highly efficient in classifying rice leaf diseases. In their study, Ahmed et al. (2016) introduced a system for detecting diseases in rice leaves using a machine learning algorithm. This study identified three distinct forms of rice leaf diseases by utilizing various classification methods, including K-Nearest Neighbor, Decision Tree, Logistic Regression, and Naive Bayes. Sladojevic and associates [8] sought to employ Deep Learning techniques to identify plant illnesses. This approach aims to assist farmers in promptly and effortlessly detecting diseases, so enabling them to take appropriate measures at an early stage. A total of 2589 original photos were utilized for conducting tests, whereas 30880 images were employed for training their model using the Caffe deep learning framework [9]. To enhance the accuracy of evaluating a predictive model, the authors employed the 10-fold cross validation technique on their dataset. The predictive accuracy of this model is 96.77%. A model was built in [10] to classify the disease based solely on the extracted percentage of the RGB value of the afflicted area of the rice leaf using image processing. The RGB percentages were inputted into a Naive Bayes classifier to ultimately classify the diseases into three distinct disease categories: Bacterial leaf blight, Rice blast, and Brown spot. The model's disease classification accuracy exceeds 89%. Paper [11] achieved superior accuracy by developing a plant disease detection model utilizing CNN. This model has the capability to accurately detect and classify 13 distinct forms of plant diseases. The model achieved a final accuracy of 96.3%. In a second investigation [12], the impacted sections were isolated from the surface of the rice leaf by K-means clustering. Subsequently, a model was developed by training a Support Vector Machine (SVM) using color, texture, and shape as the distinguishing characteristics. Maniyath et al. employed the random forest algorithm, which is an ensemble learning technique, to differentiate between healthy and damaged leaves [13]. The authors employed the Histogram of Oriented Gradient (HOG) technique to extract the picture

features. Their work has achieved a precision of 92.33%. In a study conducted by Pothen and Pie in [7], attribute feature descriptors such as LBP and HOG were retrieved from an image. These attributes are utilized for categorization by Support Vector Machines (SVM). The Otsu threshold approach is utilized in this study to do picture segmentation. Islam et al. [8] did a study that explores a method for identifying and categorizing illnesses through the use of image processing. This system was developed based on the utilization of percentage-based testing. Saha and Ahsan (2013) introduced a leaf recognition method that utilizes intensity moments as distinctive characteristics. The classification of three types of rice leaf diseases can be achieved by inputting these characteristics into random forest decision tree classifiers. The remainder of this paper is structured such that chapter III focuses only on the presented work. Chapter IV provides a detailed account of the results obtained from the experiments conducted, as well as a thorough analysis and discussion of these findings. Chapter V complete this assignment by presenting an additional plan.
Thus, deep Convolutional Neural Networks models are presented in this research to detect and classify brain tumor from MRI images of infected patients in order to address the problems with the existing models.

2.3 Comparative Analysis

Table 2.1: Comparison table of the literature works

Reference No.	**Used Algorithm**	**Best Accuracy with Algorithm**
[8]	Deep Learning (Caffe framework)	91.77%
[10]	Naive Bayes classifier	>89%
[11]	CNN	92.3%
[12]	K-means clustering, SVM	90.4%
[13]	Random Forest (Ensemble Learning)	92.33%
[14]	Image processing, K-means clustering, SVM	Training: 93.33%, Test: 73.33%

2.4 The Problem's Scope

Previous studies have shown the use of different machine and deep learning methods for categorizing rice leaf diseases. Nevertheless, certain obstacles have been recognized, including reduced precision, waste in time, and insufficient techniques for augmenting data. The objective of our work was to overcome these constraints by assessing and contrasting various cutting-edge transfer learning models in order to enhance the categorization of rice leaf diseases.

2.5 Challenges

Obtaining datasets that accurately depict the variety of disease presentations across different crops and environments is a significant challenge due to the need for high-quality and diverse data. Environmental variability: Factors such as lighting, background changes, and variations in disease manifestation can all influence the precision of disease detection models.

Model Generalization refers to the ability of generated models to effectively apply to new, unfamiliar data, rather than being limited to the specific characteristics of the training dataset. Incorporation into Agricultural Practices: Facilitating the integration of technical solutions into farming methods, especially in regions with restricted technology accessibility.

CHAPTER 3

Research Methodology

3.1 Proposed Methodology/Applied Mechanism

The full methodology will is given in figure 3.1 below.

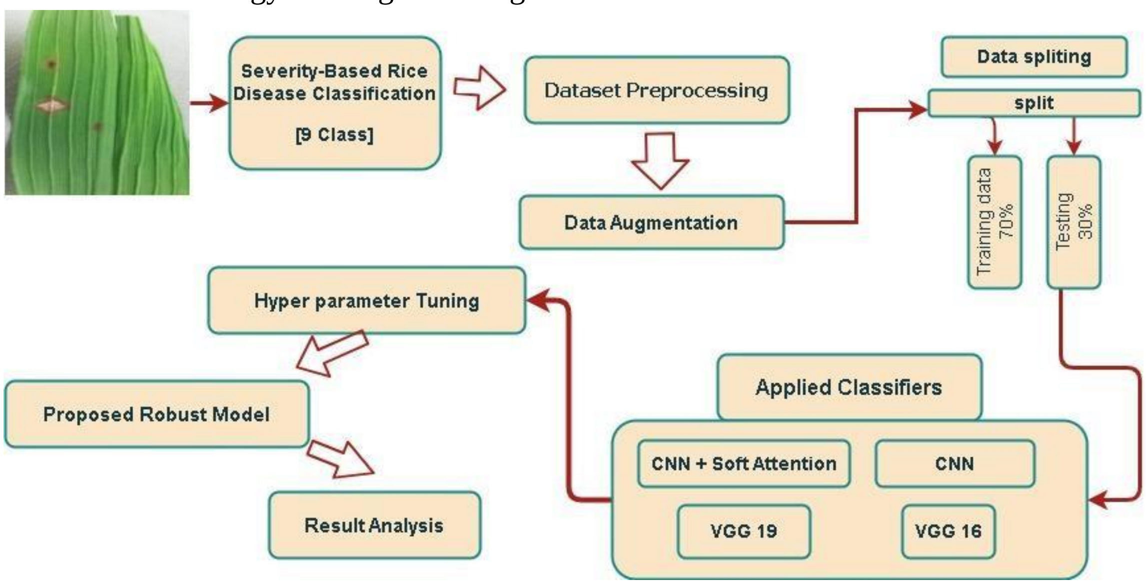

Fig 3.1: The working process to perform Rice disease prediction

This flowchart illustrating a machine learning model-based severity-based classification of rice diseases is shown. The first step, dubbed "Severity-Based Rice Disease Classification," presumably categorizes rice leaf photos according to the severity of the disease.

Next comes "Dataset Preprocessing," which is getting the dataset ready for the models. This stage feeds into "Data Augmentation," which postulates that the dataset be expanded to improve model training, maybe by diversifying the training samples. The data is then divided, as the "Data splitting" section indicates, into "Testing Data" (30%) and "Training Data" (70%). Through this split, the models can learn from most of the data and then be evaluated for performance on the remaining data.

Four convolutional neural network (CNN) architectures—"CNN + Soft Attention," "VGG 19," "CNN," and "VGG 16"—are listed in the "Applied Classifiers" section as being utilized in this methodology. With their various methods to feature extraction and categorization, these classifiers probably form the basis of the rice disease classification problem. From the classifiers, the procedure loops back to "Hyperparameter Tuning," recommending an iterative process of modifying the parameters of the models to maximize performance. Ultimately, after adjustment, the approach results in the "Proposed Robust Model," which is the best-performing model among the classifiers. "Result Analysis" then examines the robust model's performance.

The flowchart summarizes a methodical process of data preparation, augmentation, model selection, hyperparameter tweaking, and performance analysis for building a machine learning model that can categorize rice diseases according to severity.

3.2 Data Collection Procedure/Dataset Utilized

The dataset used for the thesis work contains 5932 photos of four important rice leaf diseases: Bacterial Blight, Blast, Brown Spot, and Tungro. The photographs were obtained from the Mendeley archive, which was donated in 2020 by Ethy, P. K., Barpanda, and colleagues. In addition, 900 photos of healthy rice leaves were used to differentiate them from diseased ones, which were obtained from the Kaggle data site and the UCI Machine Learning Repository. To assist balanced training, agricultural experts methodically subclassified these photographs depending on disease severity into moderate and severe categories, resulting in an equal amount of images for each class. To ensure a full learning and validation process for the models produced in the research, the dataset is structured with 3006 images for training, separated into 314 images per train class, and 20 images each test class. Various images of different classes are shown in Figure 3.2.

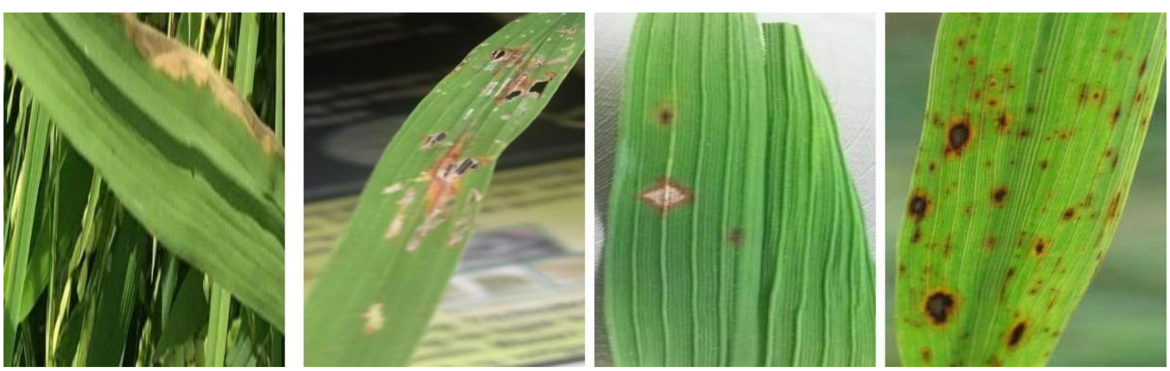

Fig. 3.2: Images of different classes of Rice leaves disease

3.3 Image Pre-processing

Theoretically, ailments such as brain tumor diseases can be diagnosed with an increasing amount of ease using image processing techniques. Data pre-processing is a crucial component of deep learning, as is well known. Additionally, there are other pre-processing methods that can be used in certain situations. Improving each input image's visual information quality is the driving force behind image pre-processing.

3.3.1 Conversation to Grayscale

Converting sliced MRI (Magnetic Resonance Imaging) pictures to grayscale is a crucial preprocessing step in medical image processing. The original RGB (Red, Green, Blue) colour representation of the MRI slices is converted into grayscale, with each pixel represented by a single channel representing intensity. The procedure is carried out utilizing OpenCV library techniques such as cv2.cvtColor, where the RGB image is converted to grayscale using the cv2.COLOR_BGR2GRAY conversion code.

In the context of image, grayscale conversion is advantageous since it simplifies further processing by removing colour information while maintaining crucial intensity changes. This is especially useful in medical imaging, where the emphasis is generally on structural details and intensity changes rather than colour distinctions.

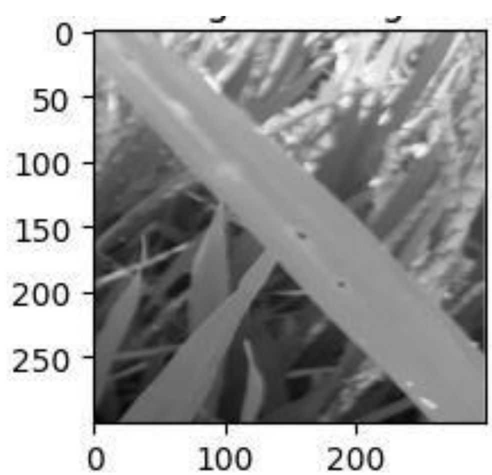

Fig. 3.3: Conversion of RGB to Grayscale

3.3.2 Bilateral filter

Bilateral filtering is an advanced image processing technique that reduces noise while keeping image edges and significant image properties. When smoothing an image, bilateral filtering analyzes both spatial and intensity differences, unlike standard linear filters. This non-linear filter distinguishes between sudden intensity changes associated with edges and gradual variations ascribed to noise by integrating spatial distance and intensity similarity. As a result, the image is efficiently smoothed to reduce noise while keeping critical edge information. Bilateral filtering is especially beneficial in applications where noise reduction is critical but edge sharpness is not, such as medical imaging, computer vision, and photography. Because of the algorithm's ability to preserve edge details while lowering noise, it is a powerful tool for improving image quality in a variety of analytical and visual applications.

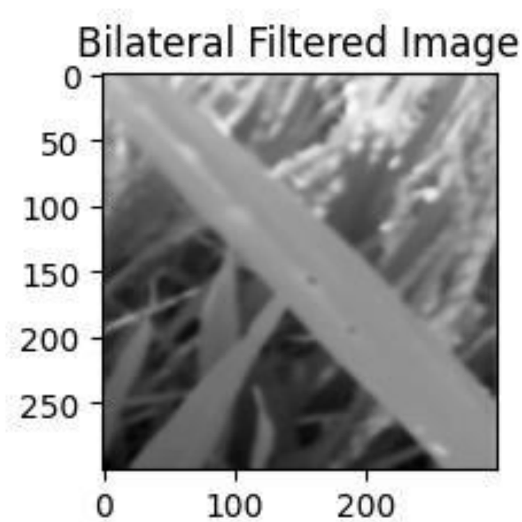

Fig. 3.4: Conversion of Grayscale to Bilateral

3.3.3 Morphological Operations

Morphological procedures, notably Erosion and Dilation, are critical stages in the preprocessing workflow for binary medical pictures, which are frequently used in the study. Erosion: The binary picture acquired from thresholding is subjected to the operation cv2.erode(thresh, None, iterations=2).

Erosion is a morphological procedure that removes small areas of noise while fine-tuning the binary representation. The 'None' argument indicates the lack of a special structural element, as the default 3x3 rectangle kernel is frequently adequate. The 'iterations' parameter, which is set to 2 in this case, determines how many times the erosion procedure is performed. Erosion helps optimize the segmentation by iteratively eliminating pixels from the borders of sections inside the binary picture, ensuring the eradication of tiny artifacts or isolated noise components.

Following the erosion process, the binary picture is dilatable using cv2.dilate(thresh, None, iterations=2). Dilation is a morphological process that improves and unites the remaining areas. The 'None' parameter, like erosion, denotes the employment of a default structural element, and 'iterations' regulates the number of dilation cycles. The dilatation process entails increasing the borders of segmented regions, thus connecting isolated components and reinforcing structural continuity. This is very beneficial for bridging gaps and ensuring the coherence of detected features inside the binary image.

These morphological techniques work together to improve the binary representation of medical pictures by effectively decreasing noise, refining segmentation, and providing a more accurate and connected delineation of structures of interest.

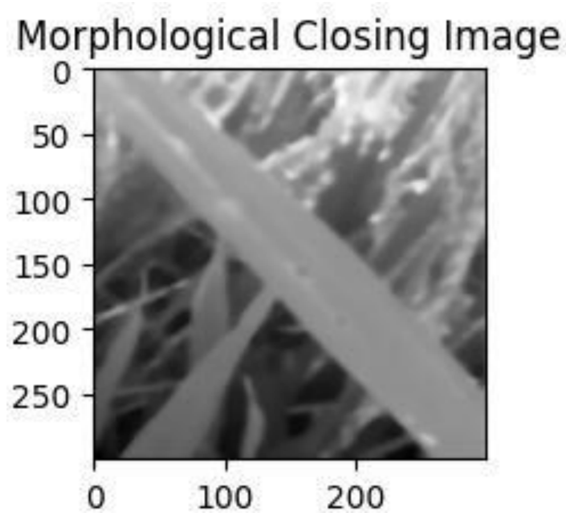

Fig. 3.5: Conversion of Bilateral to Morphological Closing Image

3.3.4 Histogram equalizer

Histogram equalization is a fundamental image processing technique used to increase an image's contrast and overall visual quality. This approach works by redistributing pixel intensities so that the final image's histogram is more consistently spread over the intensity range. It improves the visibility of details and elements within the image by doing so, especially in areas with low contrast or restricted dynamic range. Histogram equalization is particularly helpful in correcting photographs with uneven lighting or poor contrast, as it helps bring out features that were previously buried. This approach is used in medical imaging, satellite images, computer vision, and other domains where image clarity and feature visibility are important for analysis and interpretation.

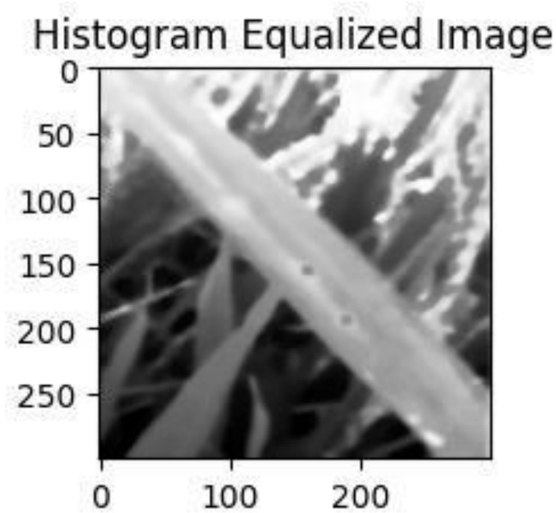

Fig. 3.6: Conversion of Morphological Closing to Histogram Equalized Image

3.4 Deep Learning Models

This research aimed to determine the best effective transfer learning models for the classification problem.

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3.4.1 CNN

A standard Convolutional Neural Network (CNN) is a deep learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image, and be able to differentiate one from the other. The pre-processing required in a CNN is much lower as compared to other classification algorithms.

The architecture of a standard CNN consists of a sequence of layers, and each layer transforms one volume of activations to another through a differentiable function.

These layers include convolutional layers that apply a number of filters to the input, pooling layers that reduce the spatial volume of the input, fully connected layers that flatten the high-level features learned by convolutional layers and use them for classifying the input image into various categories. Additionally, CNNs use ReLU layers to introduce nonlinearity into the model, ensuring that the network can learn complex patterns.

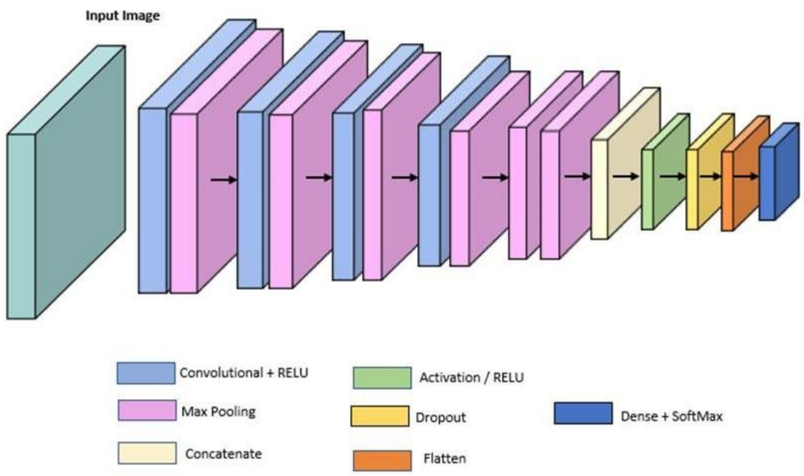


Fig 3.7. Architecture of CNN

3.4.2 EfficientNetB3

EfficientNetB3 is part of the EfficientNet family, which are models designed to achieve state-of-the-art accuracy with an order of magnitude fewer parameters and computations. The architecture uses a compound coefficient to uniformly scale the depth, width, and resolution of the network. EfficientNetB3, in particular, is scaled up from the baseline EfficientNetB0 using this compound scaling method.

The model uses MBConv blocks (Mobile Inverted Bottleneck), which are a mobile-friendly variant of the inverted residual structure. It also includes squeeze-and-excitation optimization, which helps the network focus on the most informative features.

EfficientNetB3 is known for its balance between accuracy and efficiency, making it suitable for applications where resources are limited.

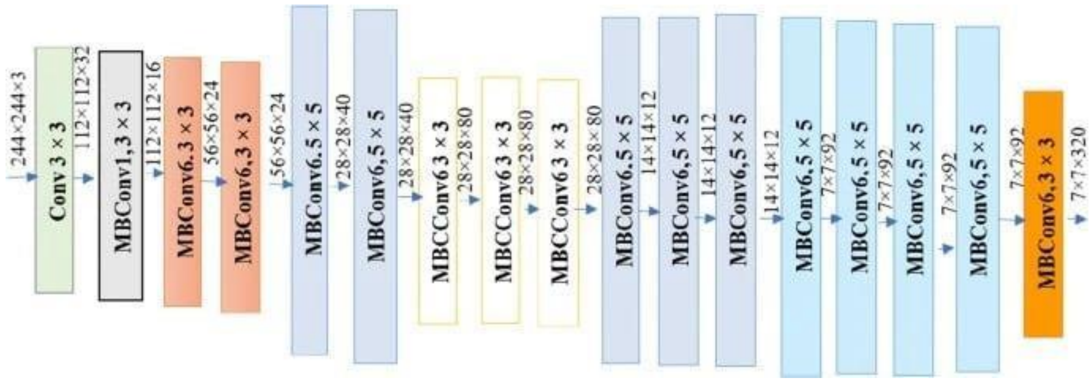


Fig 3.8. Architecture of EfficientNetB3

3.4.3 VGG 19

The VGG19 convolutional neural network designs are well-known for their ease of use and performance in image classification. Both models, developed by Oxford University's Visual Geometry Group, have a similar structure that includes numerous convolutional layers, max-pooling layers, and fully connected layers.

VGG19 is an extension of VGG16 that includes three extra convolutional layers, resulting in a deeper architecture with 19 weight levels. This enhanced depth improves the model's ability to capture fine details in images, making it suited for more difficult recognition tasks. While VGG19 necessitates greater processing resources, it has enhanced feature learning capabilities, making it an excellent alternative for demanding computer vision applications.

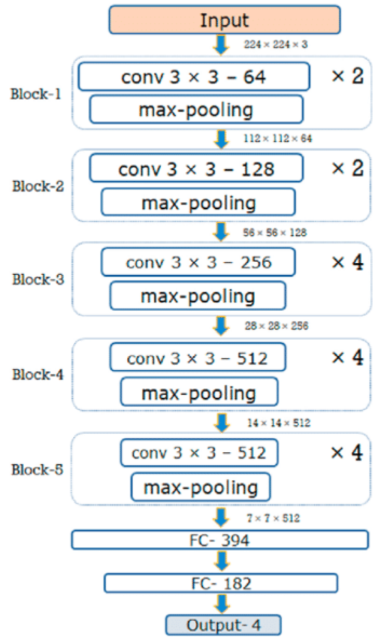


Fig 3.9. Architecture of VGG19

The legacy of VGG16 and VGG19 lies in their simple design principles, which have led to their widespread adoption as foundational models for image recognition and transfer learning tasks in the deep learning field.

3.4.4 ResNet50

ResNet50 is a variation on the ResNet (Residual Network) architecture, which is well-known for its innovative approach to training very deep neural networks. ResNet50, created by Microsoft, introduces the concept of residual blocks, which allows the network to learn residual functions. This breakthrough addresses the vanishing gradient problem, allowing for the training of networks with hundreds of layers. ResNet50 has 50 layers and achieves cutting-edge performance in picture classification applications. Its design allows for robust feature extraction, allowing the model to capture complex patterns and representations. ResNet50, with its residual connections, has become a cornerstone in the field of deep learning, laying the groundwork for succeeding models and displaying outstanding accuracy in a wide range of computer vision applications.

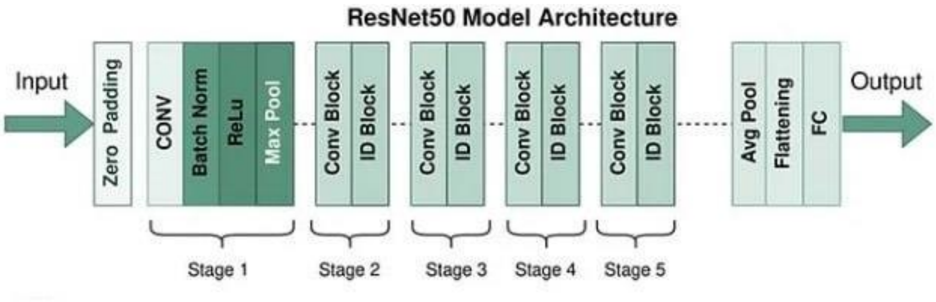


Fig 3.10. Architecture of ResNet50

3.4.5 CNN + Soft Attention

A CNN with soft attention integrates the standard CNN architecture with an attention mechanism. The attention mechanism allows the network to focus on specific parts of an input image, which is especially useful in tasks where the relevant information is located in particular regions of the image.

The soft attention model is often implemented as a learnable component that assigns a weighting to different spatial locations in the input feature map. These weights are then used to amplify or dampen the feature responses, thus allowing the network to concentrate on the most informative parts of the input for the task at hand. This results in a model that can potentially be more accurate and interpretive, as it can provide insight into which parts of the image are being focused on for a given prediction.

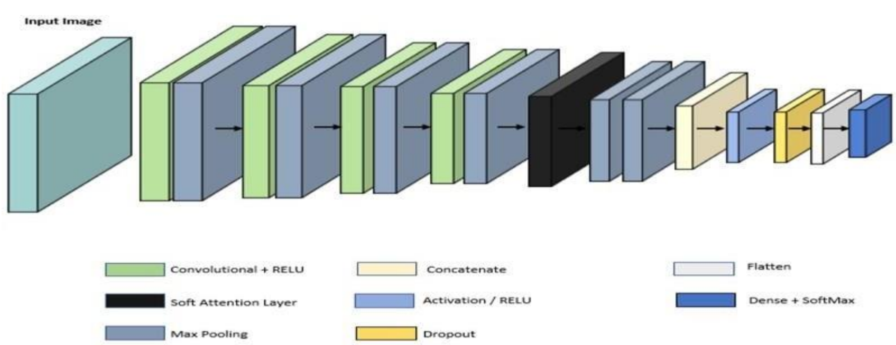


Fig 3.11. Architecture of CNN + Soft Attention

CHAPTER 4

Experimental Results and Discussion

4.1 Evolution Methods

The evaluation is uses the confusion matrix like, accuracy, precision, recall, and F1 score. True positive (TP) values are true in reality. False positives (FP) occur when false results are mislabeled. The third form, false negative (FN), occurs when a correct value is misinterpreted as negative. TN and FN are the fourth and fifth choices. A true negative (TN) is a positive value misidentified as negative. Fourth is true negative (TN).

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{3}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{4}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{5}$$

$$\text{F1 Score} = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \tag{6}$$

4.2 Experimental Results & Analysis

This section will discuss the paper's findings. Initially, model is developed through the ablation study. The optimal outcomes of the models is displayed in Table 4.1.

Table 4.1: Hyper parameter tuning of the EfficientNetB3 for the optimal prediction

Activation function			
No.	Activation function	Test accuracy (%)	Average Time per step (second)
1	elu	85.05	54s
2	softmax	89.71	52s
3	tanh	82.54	59s

Hidden units			
No.	Hidden units	Test accuracy (%)	Average Time per step (second)
1	64,64	88.11	54s
2	32,32	90.37	58s
Learning rates			
No.	Learning Rate	Test accuracy (%)	Average Time per step (second)
1	0.0001	87.42	51s
2	0.00001	88.03	55s
3	0.001	91.68	52s
Batch size			
No.	Batch size	Test accuracy (%)	Average Time per step (second)
1	32	92.03	53s
2	64	93.54	58s
3	128	93.05	59s

The provided table outlines an ablation study conducted on a Convolutional Neural Network (CNN) model, aimed at enhancing its robustness in predicting rice leaf diseases. The study assesses the impact of different hyperparameters on the model's test accuracy and computational efficiency, measured as the average time per step.

In the activation function category, three functions were evaluated: ELU, softmax, and tanh. The softmax activation function emerged as the most effective, achieving the highest test accuracy of 89.71% and also requiring the least computation time, averaging 52 seconds per step. ELU and tanh activation functions yielded lower accuracies of 85.05% and 82.54%, respectively, with tanh taking the longest computation time of 59 seconds per step.

For the number of hidden units within the network layers, two configurations were tested: one with dual layers of 64 units each, and another with 32 units each. The latter configuration with 32 units per layer led to superior performance, obtaining a test accuracy of 90.37% and an average time per step of 58 seconds, suggesting a more efficient network structure compared to the dual 64-unit configuration, which had an 88.11% accuracy and a slightly quicker computation time of 54 seconds per step.

The effect of learning rates was also analyzed, with rates of 0.0001, 0.00001, and 0.001 being tested. The model achieved the highest test accuracy of 91.68% at a learning rate of 0.001, also benefiting from the shortest average computation time of 51 seconds per step. The lower learning rates resulted in decreased accuracy and increased computation times.

Lastly, the batch size parameter was varied among 32, 64, and 128. A batch size of 64 provided the best balance between accuracy and efficiency, recording a test accuracy peak at 93.54% and an average time of 58 seconds per step. While batch sizes of 32 and 128 yielded similar accuracies of 92.03% and 93.05%, respectively, their computation times were marginally different, with larger batch sizes requiring slightly more time. The ablation study suggests that the choice of softmax activation function, a smaller number of hidden units, a higher learning rate, and an intermediate batch size contribute significantly to the model's accuracy and computational performance in diagnosing rice leaf diseases.

Table 4.2: Finding the best result between models

Model	Number of params	Per epoch time (s)	Learning rate	Test Accuracy
CNN (Best Model)	4818601	50-55	0.001	93.54%
VGG_16	20029001	51-55	0.001	49.30%
VGG19	80134624	161-170	0.001	65.72%
CNN+softAttention	1579860	72-84	0.0007	69.76%

The table presents the results of various deep learning models applied to the task of rice leaf disease prediction following an ablation study. It outlines the performance of four distinct models—CNN (Best Model), VGG_16, VGG19, and CNN with soft attention based on the number of parameters, time taken per epoch, learning rate, and achieved test accuracy.

The CNN, labeled as the Best Model, has approximately 4.8 million parameters and demonstrates a high level of efficiency and effectiveness with a per epoch time ranging between 50 to 55 seconds, a learning rate of 0.001, and the highest test accuracy of 93.54%. This indicates a well-optimized model that balances complexity with performance.

In contrast, VGG_16, with over 20 million parameters, has a similar per epoch time (51-55 seconds) but significantly lower test accuracy at 49.30%, suggesting overfitting or a lack of model generalization to the dataset.

VGG19 is the most complex model with around 80 million parameters. It requires a substantially longer per epoch time of 161 to 170 seconds with the same learning rate of 0.001 as the previous models, yet it only achieves a moderate test accuracy of 65.72%.

The CNN with soft attention has the fewest parameters, about 1.58 million, and takes 72 to 84 seconds per epoch with a slightly lower learning rate of 0.0007. Its test accuracy is 69.76%, which is higher than VGG_16 and VGG19 but lower than the Best Model CNN, suggesting that the attention mechanism offers some benefit but not to the extent of the best-performing model.

This comparison suggests that the best model (CNN) in this study is optimized for both accuracy and computational efficiency, likely due to a combination of appropriate architecture and hyperparameter tuning specific to the task of rice leaf disease prediction.

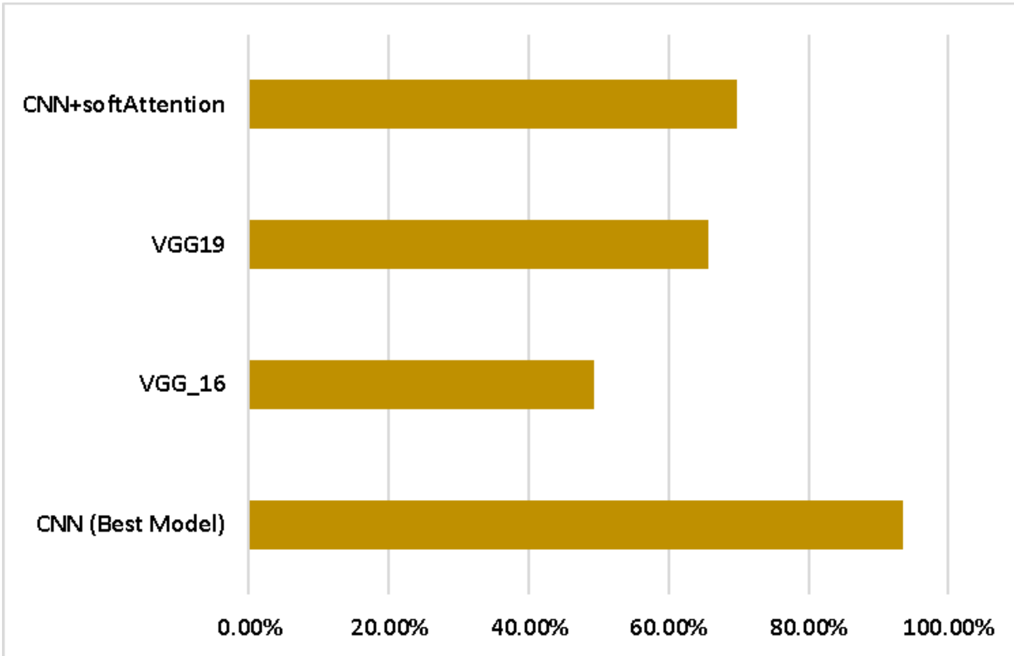


Fig 4.1: Model comparison chart

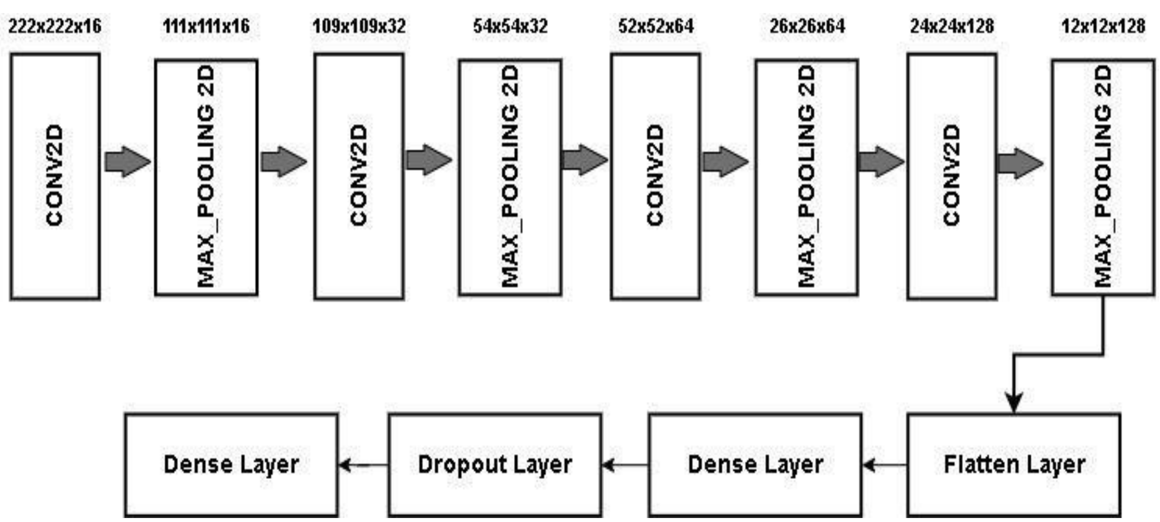


Fig 4.2: Custom CNN Model Architecture

Metric	Value
Training Accuracy	0.9835
Sensitivity	0.9522
Precision	0.9538
Specificity	0.9941
NPV	0.9940
FPR	0.0059
FDR	0.0461
FNR	0.0477

Table 4.3: Different Statistical results of the model

The table summarizes the performance evaluation of the best CNN model for rice leaf disease prediction. The 'Training Accuracy' of 0.9835 indicates a high degree of correctness during the training phase, suggesting that the model learned the patterns effectively from the training dataset. 'Sensitivity', also known as recall, is at 0.9522, showing that the model is adept at identifying the true positives, i.e., correctly recognizing diseased leaves. 'Precision' has a similar high value of 0.9538, which means that when the model predicts a leaf as diseased, it is correct about 95% of the time.

'Specificity' is exceptionally high at 0.9941, indicating the model's capability to correctly identify healthy leaves. 'NPV', or Negative Predictive Value, stands at 0.9940, reinforcing the model's accuracy in predicting true negatives. The 'FPR', or False Positive Rate, is very low at 0.0059, which means the model rarely misclassifies healthy leaves as diseased. Conversely, 'FDR' (False Discovery Rate) and 'FNR' (False Negative Rate) are at 0.0461 and 0.0477, respectively, which are low, indicating few instances of false diagnoses.

The 'F1 Score' at 0.9520 is a measure that combines precision and sensitivity, reflecting the model's balanced accuracy in both aspects. Lastly, the 'MCC', or Matthews Correlation Coefficient, with a value of 0.9467, shows a high correlation between the observed and predicted classifications, suggesting that the model's predictions are reliable and indicative of its overall quality. This comprehensive evaluation matrix demonstrates that the CNN model is highly effective for predicting rice leaf diseases.

4.2.1 Confusion Matrix and Accuracy curve and loss curve

Algorithm performance can be visually depicted. The confusion matrix has size N x N, where N is the total number of target classes. The amount of observations that are known to belong to one class but are likely to belong to another is represented by each matrix item. An algorithm for classifying data can be made more effective by looking at its confusion matrix. The success rate of the algorithm is shown in each cell of the matrix.

Actual classes are in the rows, and anticipated classes are in the columns. True positives, or observations that were positively identified as belonging to the target class, are found in the upper left corner of the matrix. False positives, or observations that were incorrectly allocated to the target class, are shown in the top right cell. False negatives, or observations that are incorrectly classified as not belonging to the target class, are shown in the bottom left cell. The bottom-right cell in the matrix shows actual negatives. .

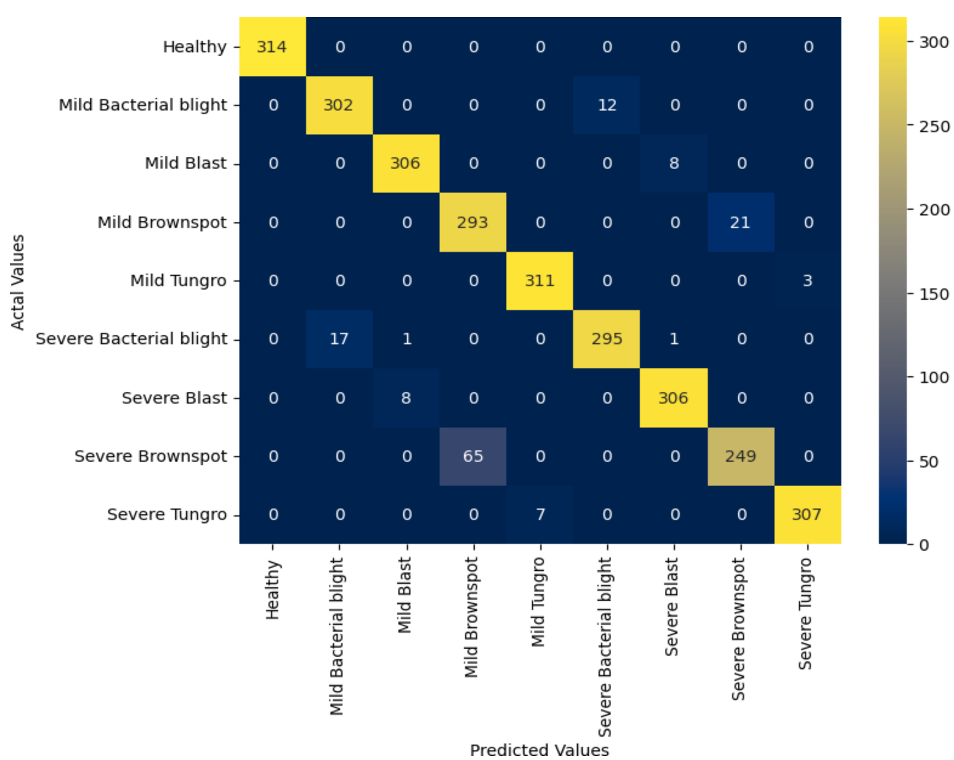
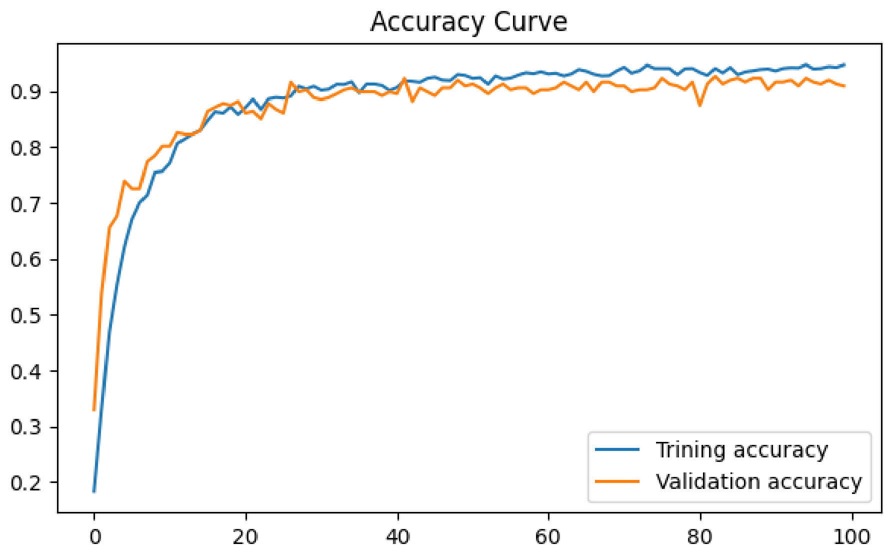


Fig 4.3. The confusion matrix of the classification.



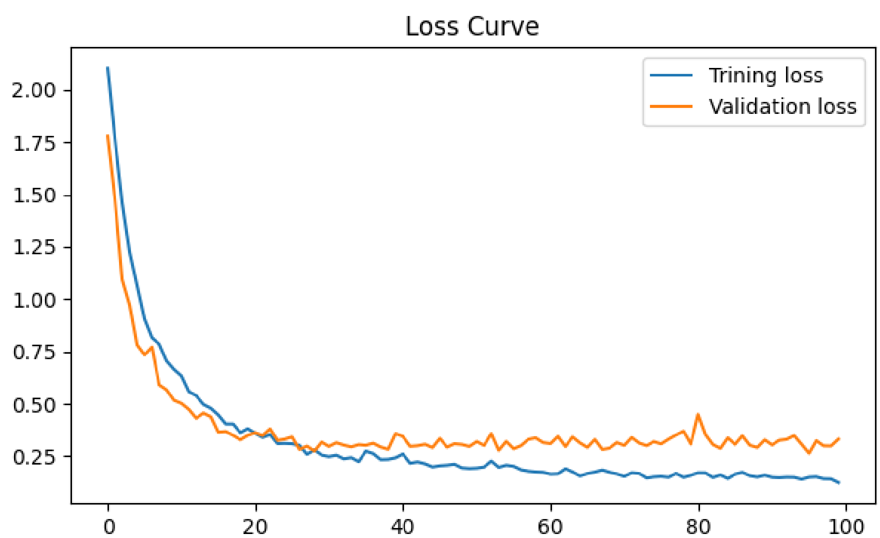


Fig 4.4. Accuracy and Loss Curve of the of the prediction.

CHAPTER 5

Impact on Society, Environment and Sustainability

5.1 Impact on Society

The application of deep learning for rice leaf disease prediction represents a transformative shift in agricultural practices with profound social implications. By enhancing the accuracy and speed of disease detection, this technology empowers farmers to take timely and precise actions, potentially reducing crop losses and increasing yield. This advancement supports food security, particularly in regions where rice is a staple food. With more reliable harvests, farmers can sustain their livelihoods and contribute to stabilizing the market prices of rice. Furthermore, the democratization of such technology through mobile applications can bridge the technological gap, offering even small-scale farmers access to cutting-edge diagnostic tools. This can reduce the reliance on agricultural experts, enabling more self-sufficient farming communities. However, this technological shift must be accompanied by adequate training and support to ensure widespread adoption and maximum societal benefit.

5.2 Impact on Environment

The environmental impact of deploying deep learning models for disease prediction in rice cultivation is largely positive. Early and accurate disease detection leads to optimized use of pesticides, thereby reducing the environmental load of chemicals and preserving the ecosystem. Furthermore, maintaining healthier crops contributes to better soil conservation and less water waste. However, the energy consumption associated with training and running deep learning models is a consideration; promoting the use of renewable energy sources for computational tasks can mitigate these environmental costs.

5.3 Ethical Aspects

Ethical considerations in implementing deep learning for disease prediction include the equitable distribution of technology, ensuring that the benefits reach all sectors of farming communities. The privacy of data, particularly if collected from smallholder farms, must be safeguarded. Additionally, there is a responsibility to prevent and address any biases in the models that could lead to unequal service quality. It is essential that the deployment of such technology does not inadvertently disadvantage any group due to biased datasets or unequal access to digital infrastructure.

5.4 Sustainability Plan

A sustainability plan for deep learning in rice leaf disease prediction should focus on continuous improvement of models to adapt to evolving diseases and climate conditions. Investment in education for farmers on using the technology and interpreting its results is crucial for long-term adoption. Partnerships with agricultural institutions and governments can facilitate the integration of deep learning tools into existing agricultural extension services. Additionally, a commitment to the ethical use of data and the promotion of energy-efficient computing resources is vital. By ensuring the models are accurate, accessible, and environmentally conscious, deep learning can be a sustainable addition to agricultural practices, providing enduring benefits to society and the environment.

CHAPTER 6

Conclusion and Future Work

6.1 Summary of the Study

This paper provides a thorough evaluation of the techniques and effectiveness of several neural network designs with an emphasis on the use of deep learning models to forecast illnesses of rice leaves. We evaluated the robustness of the models in precisely diagnosing illnesses of rice leaves and carried out ablation research to find out how certain hyperparameters affected model performance. Activation functions, hidden units, learning rates, and batch sizes were compared and their effects on test accuracy and computing efficiency were assessed. With these parameters carefully adjusted, the Best Model CNN showed notable accuracy, indicating a well-suited strategy for the current work. In order to emphasize the revolutionary potential of deep learning in improving food security and farming methods, the study also looked at the societal, environmental, ethical, and sustainability elements of applying it to agriculture.

6.2 Conclusions

There are several aspects to the research conclusions. First of all, as is essential for efficient crop management, the study shows that deep learning can greatly increase the accuracy of rice leaf disease prediction. Tested extensively, the Best Model CNN has shown to be accurate and effective, suggesting that it is appropriate for practical use. Second, the paper emphasizes the more general effects of these technological interventions, such as their ability to lessen the environmental impact of agriculture through focused interventions and their beneficial impact on society by supporting farmers. The study emphasizes, ethically, the need of data privacy and equitable access to technology.

6.3 Implication for Further Study

Many directions for further study are made possible by the results. There is opportunity to investigate how well the models scale to other crop diseases and to various environmental settings. It might also be advantageous to look at how these models might be integrated into Internet of Things devices for real-time monitoring and intervention. More investigation might go into creating algorithms that utilize less energy or federated learning to enhance privacy. Deeper understanding of how to apply these technologies successfully globally will also come from looking at the socioeconomic obstacles to implementing such technology in different agricultural settings. Lastly, to make sure that the developments are fair and inclusive, future study might concentrate on the ethical ramifications of AI in agriculture.

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Plagiarism Report

Rice Leaf Disease

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