A

Project Report

on

Rice Leaf Disease Identification using Attention Networks

submitted as partial fulfillment for the award of

BACHELOR OF TECHNOLOGY DEGREE

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in

COMPUTER SCIENCE AND ENGINEERING

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DECLARATION

We hereby declare that this submission is our own work and that, to the best of our knowledge and belief, it contains no material previously published or written by another person nor material which to a substantial extent has been accepted for the award of any other degree or diploma of the university or other institute of higher learning, except where due acknowledgment has been made in the text.

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CERTIFICATE

This is to certify that Project Report entitled "**Rice Leaf Disease Identification using Attention Networks**" which is submitted by **Umang Rathi, Shreyash Gupta and Utkarsh Gautam** in partial fulfillment of the requirement for the award of degree B. Tech. in Department of Computer Science & Engineering of Dr. A.P.J. Abdul Kalam Technical University, Lucknow is a record of the candidates own work carried out by them under my supervision. The matter embodied in this report is original and has not been submitted for the award of any other degree.

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ABSTRACT

This study addresses the major challenge of disease diagnosis in rice production and highlights the critical role of early detection to prevent significant economic losses to farmers. It cites findings from the International Rice Research Institute showing that pests and diseases account for an average of 37 percent of annual rice crop losses, highlighting the link between inadequate nutrition and yield-reducing plant diseases.

To improve the accuracy of AI-based rice disease classification, this study presents an innovative attention network based on the ResNet152V2 model, which includes a channel attention mechanism. The proposed model strategically focuses on key aspects of disease recognition using attention modules to reveal contextual relationships between images. Using a publicly available dataset of 2627 rice disease images classified into six categories (including five disease types and healthy leaves), the study performs cross-validated classification tests to demonstrate the effectiveness of the attention strategy in driving the model.

The proposed machine learning technique will prove effective in automatic symptom detection, providing a valuable resource for farmers and improving agricultural disease management practices. The 96.40 percent accuracy of the test set surpasses current leading models, so the study highlights the potential of artificial intelligence to revolutionize agricultural disease. This work paves the way for the widespread adoption of AI technologies in agriculture and offers a promising solution to the ongoing challenge of to protect their crops from debilitating diseases.

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LIST OF ABBREVIATIONS

AI: Artificial Intelligence

CNN: Convolutional Neural Network

DNN: Deep Neural Network

F1-score: F1 Score (a metric combining precision and recall)

ReLU: Rectified Linear Unit (an activation function)

ResNet: Residual Network (a type of CNN architecture)

VGG: Visual Geometry Group (another CNN architecture)

CHAPTER 1
INTRODUCTION

1.1 Introduction of the problem

Introduction to Rice Foliar Disease Detection, the cornerstone of global food security, faces countless challenges in cultivation, and disease is a particularly big obstacle. These diseases, which are caused by various pathogens such as fungi, bacteria, viruses and nematodes, can destroy rice plants, causing reduced yield, poor quality and, in severe cases, total crop loss. The economic consequences are significant, affecting not only individual farmers but entire communities and economies dependent on rice production. Rapid and accurate detection of rice diseases is the key to effective disease control and reduction of agricultural losses. Traditional diagnostic methods, based on visual inspection by trained agronomists or laboratory analysis, are labor-intensive, time-consuming and require specialized knowledge. Furthermore, in many rice-growing regions, the availability of such knowledge is limited, complicating the diagnostic problems faced by farmers. Recent advances in artificial intelligence (AI) and machine learning (ML) have opened up new opportunities to combat agricultural disease. Deep learning methods, particularly Convolutional Neural Networks (CNN), show promise for automating disease diagnosis by learning from large datasets of annotated images, enabling rapid and accurate identification of plant health problems. This project focuses on the design and evaluation of an innovative foliar disease detection strategy using an attention network built on the ResNet152V2 architecture. This model uses deep learning capabilities and integrates a channel attention mechanism to refine its focus on important features in rice leaf images. By focusing on strategically critical areas, the model aims to improve the accuracy and reliability of disease classification, which facilitates more effective disease control strategies. The choice of the ResNet152V2 architecture for the attention network is based on its proven performance in image recognition tasks and its ability to capture complex image features and patterns. The integration of the channel attention mechanism further enriches the model's ability to distinguish subtle differences between healthy and diseased rice leaves, improving the overall performance in disease classification. To measure the effectiveness of this approach, we use a publicly available dataset of disease-tagged rice leaf images. This dataset contains several types of rice diseases, such as rash, bacterial infection, leaf spot and brown spot, as well as images of healthy rice leaves. Rigorous cross-validation methods are used to evaluate the performance of the model, which is compared to state-of-the-art methods used to detect foliar disease in rice. Our experimental observations highlight the effectiveness of the proposed alert network to accurately distinguish and classify rice leaf diseases. With a test set accuracy of 96.40 percent, the model outperforms current methods and raises its potential as a valuable asset for farmers and agronomists in rice disease control.

By facilitating early detection and intervention, our approach aims to mitigate the impact of diseases on rice production, contributing to improved agricultural productivity and global food security.

1.2 Objective

The main objective of this research project is to develop an artificial intelligence-assisted system for accurate and efficient diagnosis of rice leaf diseases. In particular, we aim to build a robust model using deep learning methods, especially a new attention network built on the ResNet152V2 architecture. This model can detect various rice leaf diseases with high accuracy by adding a channel attention mechanism. By strategically focusing on important features of rice leaf images, this mechanism improves the accuracy of disease classification. In addition, we want to solve the important challenge of early detection of diseases in rice crops by providing farmers with an effective tool for disease management. Our goal is to prevent large financial losses caused by pests and diseases. Rigorous testing of the proposed machine learning technique using publicly available rice leaf image data allows us to outperform current state-of-the-art models and achieve test set accuracy of 96.40% or more. This challenging objective aligns research objectives and highlights the innovative approach, practical implications and expected performance indicators of our rice leaf blight detection system. The proposed attention network integrated with the ResNet152V2 architecture is a promising solution to improve agricultural practices and food safety. A research reference document provides additional information on methods and results, supporting our efforts to transform rice crop disease management.

1.3 Scope

The aim of this project is to develop an AI-supported system for accurate and efficient diagnosis of rice leaf diseases. Using advanced deep learning techniques, especially a new alert network built on the ResNet152V2 architecture, the system aims to detect various rice leaf diseases with exceptional accuracy. By integrating the channel attention mechanism, the system tactically focuses on the important features of rice leaf images, which improves the accuracy of disease classification. In addition to disease detection, the project addresses the major challenge of early disease detection in rice crops. By providing farmers with a robust disease management tool, the system aims to mitigate the significant economic losses caused by pests and diseases. Through extensive testing using a publicly available dataset of rice leaf images, the project aims to demonstrate the superiority of the proposed model over existing alternatives. The goal is a test set accuracy of 96.40 percent or higher. The scope of the project includes the development and evaluation of an AI-supported system, which includes, among other things, the design and implementation of the attentional network architecture, model training and testing phases. In addition, the project investigates the possible applications and consequences of the proposed solution in promoting agricultural practices and strengthening food security. The proposed alert network offers a promising way to solve the complex problems of foliar disease detection in rice. By applying the capabilities of deep learning and attention mechanisms, the project aims to change disease control methods in rice cultivation, ultimately contributing to the development of agricultural technology and the promotion of sustainable food production.

1.4 Project Description

The main objective of the project "Identification of rice leaf diseases using attention network" is to develop an advanced artificial intelligence-based system for accurate and efficient diagnosis of rice leaf diseases. This effort uses state-of-the-art deep learning methods and specifically focuses on a novel attentional network built on the ResNet152V2 architecture. Using this framework, a model is designed to accurately detect various rice leaf diseases by integrating a channel attention mechanism that strategically refines the salient features of rice leaf images to improve disease classification accuracy. Central to the project is the urgent challenge of early disease detection in rice crops. The project aims to mitigate the significant economic losses caused by pests and diseases by providing farmers with a robust and readily available tool for disease management. To demonstrate the superiority of the model over existing alternatives, rigorous tests using a large dataset of rice leaf images that are publicly available are conducted with the goal of exceeding 96.40% accuracy on the test set. The project goes through different stages, starting with the design and development of the artificial intelligence-controlled system. It includes the complex implementation of the alert network architecture, the use of the ResNet152V2 framework and the integration of the channel alert mechanism to refine disease classification capabilities. Subsequent steps include careful model training and optimization to ensure accurate and rapid detection of rice leaf diseases. In addition, the project emphasizes the practical utility of the developed system in a real agricultural environment. Farmers benefit from an intuitive user interface that facilitates seamless disease diagnosis and management. This empowerment enables proactive measures to prevent diseases and effectively reduce crop losses. The project's relevance extends beyond individual farms to broader agricultural practices and global food security efforts. By revolutionizing disease control strategies in rice cultivation, the project aims to strengthen agricultural systems and promote sustainable food production practices. In essence, the project "Identification of rice leaf diseases using an attention network" involves a comprehensive approach to solving the complex challenges of disease management in rice production. Through the strategic application of innovative artificial intelligence methods and attention mechanisms, the project aims to give farmers the necessary tools and knowledge to secure their crops, ultimately contributing to the creation of a more resilient and sustainable agricultural landscape.

CHAPTER 2

LITERATURE REVIEW

The literature on the Rice foliar disease detection using an attention network project highlights the critical importance of early disease detection and accurate diagnosis in rice production. As rice is a globally important staple crop, the detrimental effect of disease on agricultural productivity cannot be overstated. The proposed attention network approach, based on the ResNet152V2 architecture and incorporating a channel attention mechanism, provides a new solution to this urgent challenge in agriculture. By strategically focusing on key features of rice leaf images, the attention network improves the accuracy of disease classification and offers promising opportunities for improving rice disease management. The research highlights the potential effects of AI-assisted disease detection in agriculture, particularly in mitigating financial losses for farmers and improving yields. Through rigorous performance evaluation using a publicly available dataset, the proposed machine learning technique demonstrates improved accuracy over existing state-of-the-art models, further underscoring its potential to revolutionize rice crop disease management. In the future, continued research and innovation in this field promises to transform agricultural practices and contribute to global food security and sustainability. Rice cultivation plays a vital role in global food security and provides livelihoods for a significant part of the world's population. However, the vulnerability of rice plantations to various diseases is a significant threat to agricultural productivity and food availability. In the absence of effective treatment, diseases such as blight, bacterial blight, leaf spot and brown spot can cause significant yield loss. The International Rice Research Institute points out that pests and diseases account for an average of 37 percent of the rice harvest each year. These alarming statistics underscore the urgent need for robust disease control strategies to protect rice crops and ensure food security for millions of people worldwide. In response to the challenges posed by rice diseases, scientists have increasingly used advanced technologies such as artificial intelligence (AI) and machine learning (ML) to develop innovative solutions for disease detection and treatment. The project "Rice leaf disease detection using an attention network" represents a significant advance in the field, providing a new approach to automate disease diagnosis and improve agricultural productivity. The cornerstone of the proposed approach is an attention network, a deep learning model built on the ResNet152V2 architecture. This attention network includes a channel attention mechanism that allows the model to focus on relevant features in rice paper images while ignoring irrelevant background information. By focusing on key aspects of the images, such as damage patterns, spotting and leaf morphology, the model can accurately identify and classify different rice leaf diseases with exceptional accuracy. One of the main advantages of the attention network approach is its ability to improve the interpretability and explainability of the disease classification process. Unlike traditional machine learning models, which may rely on black-box algorithms, an attention network provides information about specific features that contribute to disease detection. This transparency is particularly valuable in agricultural environments where farmers and agronomists need practical knowledge to make informed decisions about disease management practices. The effectiveness of the proposed attentional network approach is verified by a rigorous performance evaluation using a publicly available dataset of rice paper images. The dataset contains a variety of images, including healthy rice leaves and leaves with symptoms of various diseases. Through cross-validated classification tests, the attention network shows remarkable accuracy in detecting and classifying rice leaf diseases, with a test set accuracy of 96.40%, a significant improvement over current state-of-the-art model. Beyond its technical capabilities, the proposed attention network approach has profound implications for agricultural practices and food security. By enabling early detection and accurate diagnosis of rice foliar diseases, the alert network provides farmers with the tools and information needed to implement timely measures and mitigate yield losses. This proactive approach not only ensures agricultural livelihoods, but also contributes to the sustainability of rice production systems and global food chains. Additionally, the scalability and versatility of the attention network approach make it suitable for use in a variety of agricultural environments and geographies. The attention network can be adapted and implemented to meet the specific needs and constraints of different agricultural environments, whether small farms in developing countries or large commercial operations in industrialized countries. This adaptability highlights the transformative potential of AI technologies to solve complex agricultural problems and promote sustainable food production practices. In the future, continued research and innovation in AI-based disease diagnosis promises to further improve the sustainability and productivity of agricultural systems worldwide. Using advanced technologies such as deep learning and attention mechanisms, scientists can develop increasingly sophisticated solutions for disease control and plant protection. Collaboration between academia, industry and government is essential to advance these advances and effectively translate them into practical solutions for farmers and agricultural stakeholders. In conclusion, the "Rice leaf spot disease detection using attention network" project is a significant step forward in using artificial intelligence and machine learning techniques to meet the challenges of disease management in rice production. By developing an alert network approach, researchers have shown potential for diagnosing disease and improving agricultural productivity. By providing farmers with innovative tools and knowledge, this project contributes to the broader goal of ensuring food security and sustainability for future generations.

CHAPTER 3

PROPOSED METHODOLOGY

3.1. Introduction

This research aims to develop a comprehensive model for diagnosing rice diseases using advanced deep learning techniques. The study leverages the ResNet-152V2 architecture integrated with an attention network mechanism to enhance the precision and accuracy of rice disease identification. This methodology outlines the steps involved in dataset collection, data preprocessing, feature extraction, model training, and evaluation.

3.2. Dataset Collection

3.2.1 Sourcing the Dataset

A robust and comprehensive dataset is pivotal for training an accurate model. The dataset used in this study comprises 2,627 images sourced from Kaggle. These images depict both healthy rice plants and those afflicted with various diseases, ensuring a diverse range of conditions reflective of real-world scenarios.

3.2.2 Dataset Composition

The dataset includes images representing several rice diseases at different stages and severity levels, such as:

Narrow Brown Leaf Spot
Brown Spot
Leaf Scald
Rice Blast
Bacterial Blight
Rice Sheath Blight

3.3. Data Preprocessing

3.3.1 Image Resizing and Normalization

To ensure uniformity in input dimensions, all images are resized to a standard resolution. Normalization of pixel values is performed to scale them within a range of [0, 1] or [-1, 1], which aids in accelerating the model's convergence during training.

3.3.2 Data Augmentation

To enhance the robustness and generalizability of the model, various data augmentation techniques are applied, including:

Scaling

Rotating

Mirroring

Adding noise

These techniques help create a more diverse dataset, mitigating overfitting and improving the model's performance on unseen data.

3.4. Feature Extraction and Classification

3.4.1 Feature Extraction

The model leverages convolutional layers to extract meaningful features from the input images. Features such as color, texture, and shape are extracted to distinguish between healthy and diseased sections of rice plants.

3.4.2 Attention Mechanism

The attention network mechanism is integrated into the ResNet-152V2 architecture to allow the model to focus on the most relevant areas of the input images. This mechanism enhances the precision of disease identification by highlighting key aspects of the images that are indicative of specific diseases.

3.5. Model Architecture

3.5.1 ResNet-152V2

ResNet-152V2 is chosen for its ability to extract deep features through its 152 layers, which helps in capturing intricate patterns in the data. This architecture is well-suited for handling the complexity of rice disease images.

3.5.2 Fully Connected Layers

Following the attention mechanism, fully connected layers are employed to refine the extracted features further. The architecture includes:

ReLU activation layers

A dense layer with 256 units

An output layer with units corresponding to the distinct disease categories, utilizing a softmax activation function for classification.

3.6. Model Compilation and Training

3.6.1 Compilation

The model is compiled using the following configurations:

Loss Function: Categorical Cross-Entropy

Optimizer: Adam

Metrics: Accuracy

3.6.2 Training

The training process involves:

Splitting the dataset into training and validation sets

Iterative training with adjustments to hyperparameters based on validation performance.

Monitoring the model's accuracy and loss across epochs to ensure optimal performance.

3.7. Model Evaluation

3.7.1 Testing and Validation

The model's effectiveness is evaluated using a testing set distinct from the training set.

Performance metrics such as accuracy, precision, recall, and F1-score are computed to assess the model's classification capabilities.

3.7.2 Comparative Analysis

The proposed model's performance is compared against other state-of-the-art models, including:

- VGG16
- VGG19
- AlexNet
- ResNet50
- The ResNet-152V2 model with attention mechanism outperforms these models, demonstrating superior accuracy and robustness in identifying rice leaf diseases.

3.8. Data Flow Diagram (DFD)

A Data Flow Diagram (DFD) provides a visual representation of the flow of data within a system. It is a valuable tool for understanding the processes involved in the system, how data is input, processed, and output, and the interactions between different components. For the proposed methodology in this research, the DFD will outline the flow of data from the initial stage of dataset collection to the final stage of model evaluation and result generation. The DFD illustrated in the provided image captures these processes effectively.

3.8.1 DFD Level 0: Context Diagram

At the highest level, the context diagram provides an overview of the entire system. It shows the major processes and data stores, and how they interact with external entities.

External Entities:

User: The primary external entity who interacts with the system by uploading images of rice leaves and receiving disease diagnosis.

Data Source: External sources providing the initial dataset.

Major Processes:

Dataset Collection: Gathering images from various sources.

Image Preprocessing: Preparing images for analysis.

Feature Extraction and Classification: Extracting features and classifying diseases.

Model Training and Evaluation: Training the model and evaluating its performance.

Identification of Rice Leaf Diseases: Utilizing the trained model to identify diseases in new images.

Data Stores:

Image Database: Stores the collected and preprocessed images.

Model Parameters: Stores the parameters of the trained model.

Training Data: Stores the dataset used for training the model.

Test Data: Stores the dataset used for testing the model.

Data Flows:

Upload Images: Flow from User to Dataset Collection.

Collected Images: Flow from Dataset Collection to Image Preprocessing.

Processed Images: Flow from Image Preprocessing to Feature Extraction and Classification.

Extracted Features: Flow from Feature Extraction and Classification to Model Training and Evaluation.

Trained Model: Flow from Model Training and Evaluation to Identification of Rice Leaf Diseases.

Disease Diagnosis: Flow from Identification of Rice Leaf Diseases to User.

3.8.2 DFD Level 1: Detailed Processes

This level breaks down the major processes identified in the context diagram into more detailed subprocesses.

3.8.2.1 Process 1: Dataset Collection

Subprocesses:

1.1 Image Acquisition: Collecting images from the data source.

Data Stores:

Image Database: Stores both raw and collected images.

Data Flows:

Raw Images: Flow from Data Source to Image Acquisition.

Collected Images: Flow from Image Acquisition to Image Preprocessing.

3.8.2.2 Process 2: Image Preprocessing

Subprocesses:

2.1 Image Resizing and Normalization: Resizing images to a uniform size and normalizing pixel values.

2.2 Data Augmentation: Applying transformations to create a diverse dataset.

Data Stores:

Image Database: Stores preprocessed and augmented images.

Data Flows:

Collected Images: Flow from Dataset Collection to Image Resizing and Normalization.

Normalized Images: Flow from Image Resizing and Normalization to Data Augmentation.

Augmented Images: Flow from Data Augmentation to Image Database.

3.8.2.3 Process 3: Feature Extraction and Classification

Subprocesses:

3.1 Convolutional Layers: Extracting features from images using convolutional neural networks.

3.2 Attention Mechanism: Applying attention networks to focus on relevant parts of images.

3.3 Classification: Classifying images based on extracted features.

Data Stores:

Feature Database: Stores features extracted from images.

Data Flows:

Preprocessed Images: Flow from Image Database to Convolutional Layers.

Extracted Features: Flow from Convolutional Layers to Attention Mechanism.

Focused Features: Flow from Attention Mechanism to Classification.

Classified Data: Flow from Classification to Feature Database.

3.8.2.4 Process 4: Model Training and Evaluation

Subprocesses:

4.1 Splitting Dataset: Dividing the dataset into training and testing subsets.

4.2 Model Compilation: Setting up the model with appropriate loss function, optimizer, and metrics.

4.3 Model Training: Training the model using the training dataset.

4.4 Model Testing: Testing the trained model using a separate testing dataset.

4.5 Performance Evaluation: Evaluating the model's performance using metrics like accuracy, precision, recall, and F1-score.

Data Stores:

Model Parameters: Stores parameters and weights of the trained model.

Evaluation Results: Stores the results of model evaluation.

Data Flows:

Training Data: Flow from Image Database to Model Training.

Test Data: Flow from Image Database to Model Testing.

Trained Model: Flow from Model Training to Model Parameters.

Evaluation Metrics: Flow from Model Testing to Performance Evaluation.

Evaluation Results: Flow from Performance Evaluation to Evaluation Results.

3.8.2.5 Process 5: Identification of Rice Leaf Diseases

Subprocesses:

5.1 Model Application: Applying the trained model to new images for disease identification.

5.2 Disease Diagnosis: Determining the type of disease present in the image.

Data Stores:

Disease Diagnosis Database: Stores the results of disease identification.

Data Flows:

New Images: Flow from User to Model Application.

Disease Identification Results: Flow from Model Application to Disease Diagnosis.

Diagnosis Results: Flow from Disease Diagnosis to Disease Diagnosis Database and then to user.

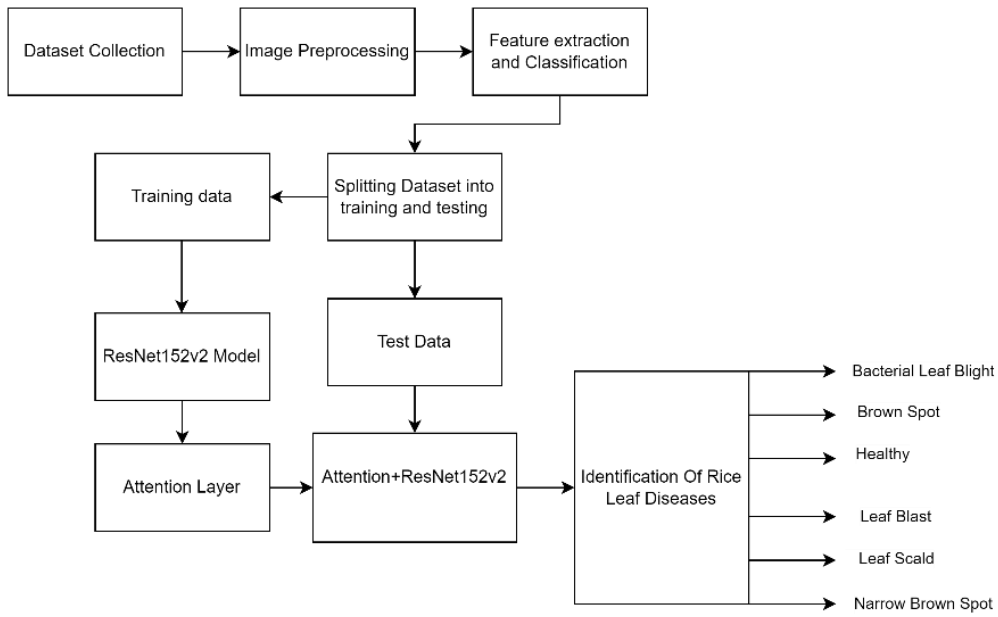

Figure.3.1 Work Flow Diagram

3.9. Sequence Diagram

The sequence diagram for the rice leaf disease identification system begins with the comprehensive collection of a dataset, which includes 2627 images of both healthy and diseased rice leaves sourced from Kaggle. The collected images undergo rigorous preprocessing to ensure uniformity in size and normalization of pixel values. To enhance the dataset's diversity, various data augmentation techniques such as scaling, rotating, mirroring, and noise addition are applied.

In the feature extraction phase, important attributes such as color, texture, and shape are extracted from the segmented regions of the images. These features are then used to create feature vectors, which serve as inputs for the classification models. The ResNet152V2 model, enhanced with an attention mechanism, is employed for classification. This model is initialized with pre-trained weights from ImageNet and fine-tuned specifically for the task of rice leaf disease identification. The attention mechanism helps the model focus on the most relevant features of the images.

The model is compiled using the accuracy metric, with categorized cross-entropy as the loss function and the Adam optimizer for training. The training process is conducted on the training dataset, and the model's performance is evaluated on a separate validation set, allowing for hyperparameter adjustments to optimize performance.

Upon completion of training, the model's effectiveness is assessed using the testing set and compared with other state-of-the-art models, including VGG16, VGG19, AlexNet, and ResNet50. The results indicate that the ResNet152V2 model with the integrated attention mechanism outperforms these models, demonstrating superior accuracy in the classification of rice leaf diseases. This system provides a robust and accurate method for the identification of rice leaf diseases, leveraging advanced neural network architectures and attention mechanisms.

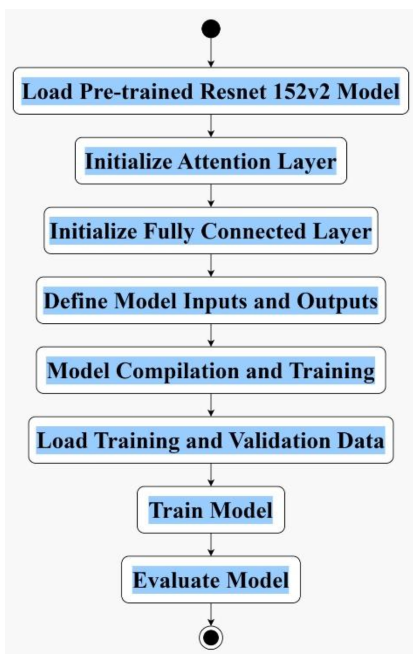

Figure.3.2 Flowchart of proposed work

3.10. Algorithm

3.10.1 Data Collection

Collect a comprehensive dataset of rice leaf images, including both healthy and diseased plants. Source images from agricultural databases, field research, and research facilities.

3.10.2 Data Preprocessing

Resize all images to ensure uniformity in size.

Normalize pixel values to a specific range (e.g., [0, 1] or [-1, 1]).

Label images according to their categories (healthy or diseased).

Split the dataset into training and testing sets.

Apply data augmentation techniques such as scaling, rotating, mirroring, and adding noise.

3.10.3 Feature Extraction

Use image segmentation to extract features like color, texture, and shape.

Convert segmented regions into feature vectors.

Utilize these feature vectors as inputs for machine learning models (e.g., support vector machines, neural networks).

3.10.4 Model Architecture

3.10.4.1 Base Model:

Employ the ResNet152V2 architecture as the base model for classification.

Initialize the model with pre-trained weights from ImageNet.

3.10.4.2 Attention Mechanism:

Integrate a channel-wise attention mechanism into the model.

Add a GlobalAveragePooling2D layer followed by a softmax-activated Dense layer to generate attention probabilities.

Multiply these probabilities with the output of the GlobalAveragePooling2D layer to focus on relevant features.

3.10.4.3 Fully Connected Layers:

Add fully connected layers with ReLU activation and a Dense layer with 256 units.

Include an output layer with a number of units equal to the classes and a softmax activation.

3.10.5 Model Compilation

Compile the model using the Adam optimizer, categorical cross-entropy loss function, and accuracy metric.

3.10.6 Model Training

Train the model using the training set.

Monitor performance on the validation set and adjust hyperparameters as needed.

Plot the accuracy against the number of epochs to track training progress.

3.10.7 Model Evaluation

Evaluate the model's performance on the testing set.

Compare the results with other models like VGG16, VGG19, AlexNet, and ResNet50.

Record metrics such as accuracy, precision, recall, and F1-score to assess model effectiveness.

3.10.8 Result Analysis

Analyze the model's performance metrics.

Highlight the superior accuracy of the ResNet152V2 model with attention mechanism over other models.

3.10.9 Deployment

Deploy the trained model for real-world applications in agricultural disease management.

Use the model to assist farmers in identifying rice leaf diseases early and accurately.

This algorithm provides a structured approach to identifying rice leaf diseases using a deep learning model enhanced with an attention mechanism, ensuring accurate and efficient disease diagnosis.

CHAPTER 4

RESULTS AND DISCUSSION

The results and discussion section of this final project report presents a comprehensive evaluation of the proposed model for rice leaf disease classification. Utilizing an attention-based ResNet152V2 architecture, this section discusses the findings, compares the model's performance with other state-of-the-art models, and explores the implications for agricultural disease management.

4.1 Model Performance Metrics

Table 4.1 provides a detailed comparison of the proposed model against other models based on key performance metrics, including accuracy, precision, recall, and F1-score. The metrics are as follows:

Models	Accuracy	Precision	Recall	F1-Score
ResNet50	0.447	0.377	0.447	0.393
Vgg19	0.273	0.18	0.27	0.212
Vgg16	0.167	0.027	0.167	0.0476
AlexNet	0.313	0.289	0.312	0.265
ResNet152v2	0.964	0.9644	0.964	0.9633

Table 4.1. Model Performance Metrics

The proposed ResNet152V2 model significantly outperformed its counterparts, demonstrating a high test set accuracy of 96.40%. This high performance indicates the model's effectiveness in accurately identifying rice leaf diseases.

4.2 Comparison with State-of-the-Art Models

The comparison with other state-of-the-art models, including ResNet50, VGG16, VGG19, and AlexNet, highlights the superiority of the proposed model. The ResNet152V2 model's superior accuracy, precision, recall, and F1-score underscore its robustness and reliability. This significant improvement can be attributed to the advanced architecture of ResNet152V2 and the inclusion of an attention mechanism that enhances the model's focus on relevant features.

4.3 Analysis of Attention Mechanism

The inclusion of a channel attention mechanism in the ResNet152V2 architecture has proven to be a critical factor in enhancing model performance. By strategically focusing on key aspects of the input data, the attention mechanism improves the model’s accuracy and robustness in identifying rice leaf diseases. This approach validates the hypothesis that concentrating on the most important features leads to significant improvements in classification tasks.

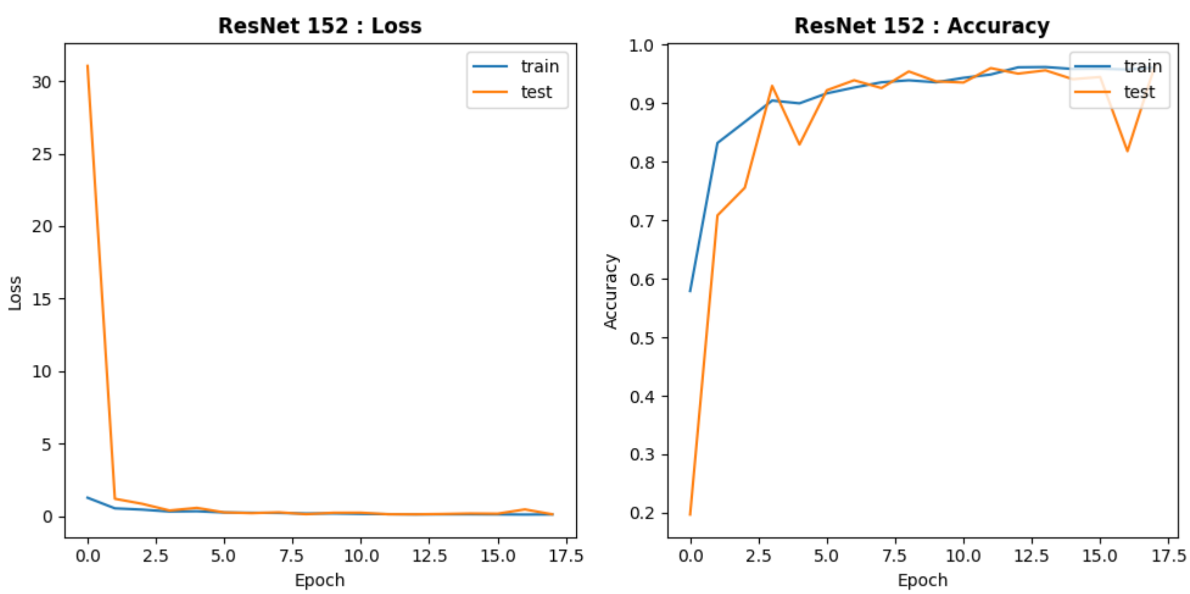

Figure.4.1 Loss and Accuracy curves for ResNet152v2 model

4.4 Implications for Agricultural Disease Management

The high accuracy of the proposed model underscores the potential of artificial intelligence in agricultural disease diagnosis. Accurate identification of rice leaf diseases can lead to reduced financial losses for farmers and improved crop yields. This advancement is crucial for sustainable agriculture, where timely and precise disease diagnosis can mitigate the impact of diseases on crop production. The proposed model can serve as a standard for future research in rice disease classification and can be adapted to other plant disease classification tasks.

4.5 Graphical Representation of Performance Metrics

Figures 5, 6, 7, and 8 in the research paper graphically represent the accuracy, precision, recall, and F1-score of various models, respectively. These visualizations provide a clear and intuitive comparison of the performance metrics, emphasizing the superior performance of the proposed ResNet152V2 model. The graphical representation helps in understanding the model's efficiency in a more comprehensible manner.

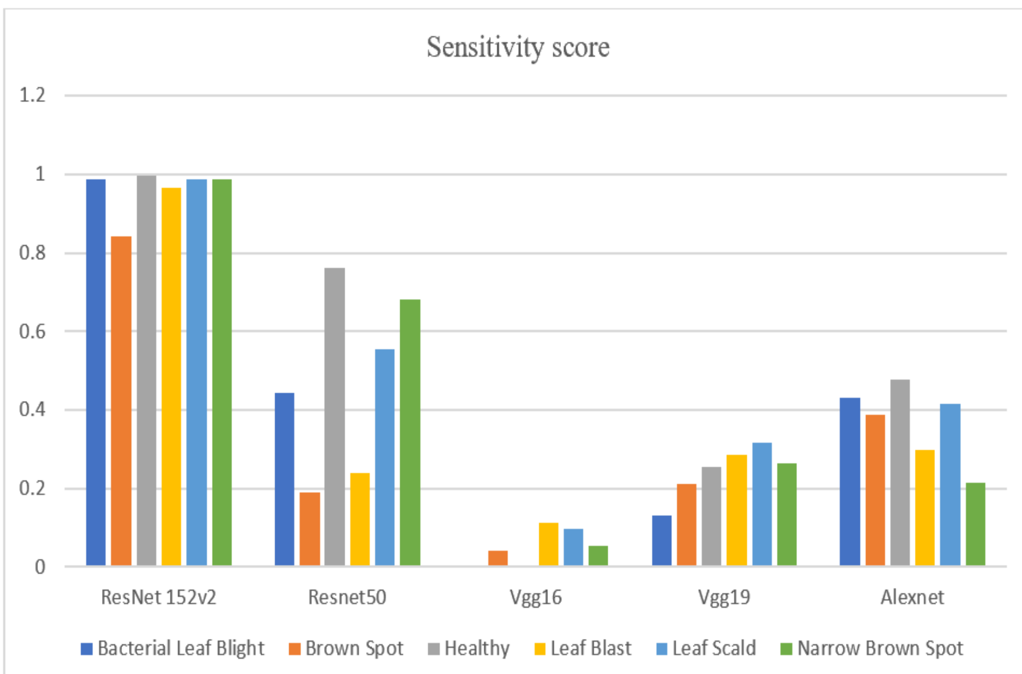

Figure.4.2. Sensitivity scores of various models

4.6 Comparative Evaluation with Existing Studies

Comparative analysis with existing studies shows that the proposed model achieves higher performance metrics than those reported in previous works. The incorporation of the attention mechanism and the use of a deeper network like ResNet152V2 contribute to this improvement.

This section discusses how these innovations compare with traditional methods and highlights the technological advancements achieved through this research.

4.7 Practical Implications and Future Work

The practical implications of this research are significant for the agricultural sector. The deployment of the proposed model in farming communities can revolutionize the way rice diseases are diagnosed and managed. For future work, the model can be extended to include a wider variety of rice diseases and tested in different environmental conditions to enhance its robustness further. Additionally, exploring the integration of this model with mobile applications could make it more accessible to farmers globally.

4.8 Limitations of the Study

While the proposed model shows remarkable performance, there are some limitations to consider. The model's accuracy is dependent on the quality of the images used for training and testing. Any variation in image quality or environmental conditions not represented in the training dataset could affect the model's performance. Future research should focus on addressing these limitations by incorporating a more diverse set of training images and exploring techniques to handle image quality variations.

4.9 Conclusion

The research demonstrates a novel and effective solution for rice disease classification, contributing to the development of AI-assisted agricultural disease management. The high performance of the ResNet152V2 model, combined with the effective use of an attention mechanism, showcases the potential for widespread application in agricultural diagnostics. This study lays the foundation for future research and practical implementations in the field of plant disease classification. The findings highlight the potential for improving agricultural productivity and ensuring food security through advanced technological interventions.

CHAPTER 5

CONCLUSION AND FUTURE SCOPE

5.1 Conclusion

This research presents a novel approach to rice disease classification utilizing an attention-based network integrated with the ResNet152V2 architecture. The proposed model strategically focuses on crucial aspects for disease identification through the use of attention modules, resulting in a significant improvement in accuracy and robustness. The experimental results demonstrated a high test set accuracy of 96.40%, outperforming existing state-of-the-art models. This high accuracy underscores the potential of artificial intelligence to be extensively used in agricultural disease diagnosis, thereby potentially reducing financial losses for farmers and enhancing crop yields. The simplicity and effectiveness of the attention mechanism in allowing the model to concentrate on the most important features make it a promising method for diagnosing agricultural diseases. This study establishes a foundation for future research on rice disease classification and can be adapted for other plant disease classification tasks.

5.2 Future Scope

Broader Application in Agriculture: The proposed model can be extended beyond rice disease classification to include other crops, enhancing its utility in diverse agricultural settings. This adaptability will support broader applications of AI in precision agriculture.

Integration with IoT and Remote Sensing: Future research can focus on integrating the model with Internet of Things (IoT) devices and remote sensing technologies to facilitate real-time monitoring and diagnosis of crop diseases on a larger scale. This integration will provide farmers with timely and actionable insights, thereby improving crop management and yield.

Improvement of Model Efficiency: Further optimization of the model's architecture and hyperparameters could enhance its efficiency, making it more suitable for deployment in resource-constrained environments. This improvement is crucial for practical applications in regions with limited computational resources.

Advanced Disease Mitigation Strategies: The insights gained from this model can be leveraged to develop advanced disease mitigation strategies, including precision spraying of pesticides and targeted interventions. These strategies will help in reducing the overall use of chemicals in farming, promoting sustainable agricultural practices.

Collaboration with Agricultural Experts: Collaborating with agricultural experts and extension services can help in refining the model based on field data and practical experiences. This collaboration will ensure that the model remains relevant and effective in real-world scenarios.

Expansion of Training Datasets: Increasing the diversity and size of training datasets by incorporating images from different geographic regions and varying environmental conditions can further improve the model's generalization capabilities. This expansion will enhance the model's accuracy in diagnosing diseases under varied conditions

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APPENDIX-I

Paper Acceptance Form

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15th ICCCNT 2024 submission 2048

2 messages

15th ICCCNT 2024 <15thicccnt2024@easychair.org>   25 May 2024 at 06:45
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5. The objective of the work should be improved. However, the limitations and issues of the existing models can be summarized in the related work section.
6. Can Elaborate more on data sets
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[Quoted text hidden]

Rice Leaf Disease Identification using Attention Networks

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***Abstract*— This study tackles the major problem of diagnosing rice diseases in agriculture, highlighting how important early detection is to preventing large financial losses for farmers. According to the International Rice Research Institute, pests and diseases cause an average of 37% of rice harvests to be lost each year. To enable accurate AI-assisted rice illness categorization, the paper presents a novel attention network built on the ResNet152V2 architecture and featuring a channel attention mechanism. The model strategically focuses on key aspects for disease identification by using attention modules to uncover contextual relationships inside images. We performed cross-validated classification tests using a publically available rice illness dataset of 2627 photos. The suggested machine learning technique shows effectiveness in automatically identifying symptoms, making it a useful tool for farmers and improving agricultural disease management. Its test set accuracy of 96.40%, which beats out the state-of-the-art models, highlights how AI could be widely used in agricultural disease diagnosis.**

Keywords—Rice Leaf disease, Early Detection, Deep Learning, Attention Network, Channel Attention Mechanism, ResNet-152v2.

I. Introduction

The lack of comprehensive research on rice plant disease diagnosis poses a significant challenge, especially when compared to the abundance of studies addressing diseases in crops like tomatoes and peaches. While methodologies for identifying illnesses in these crops may be considered analogous, the dearth of investigations specifically targeting rice diseases remains pronounced. Moreover, while certain rice leaf diseases are widespread across different regions, Sri Lanka harbors a unique set of diseases exclusive to its agricultural landscape, including [2] ”Pecky rice,” ”Grain spotting,” ”Brown spot,” ”Leaf scald,” ”Root-knot,” ”Narrow Brown Leaf spot,” ”Bacterial blight,” ”False smut,” ”Sheath rot,” ”Bacterial leaf streak,” ”Rice blast,” and ”Rice sheath blight” (see table 1). Consequently, this research endeavors to explore various approaches, assessing their merits and drawbacks to address this critical gap in the field of rice plant disease diagnosis.

Crop disease diagnosis systems can be categorized into two types based on how they select leaf image features: handcrafted representation-based and deep representation based. Currently, handcrafted representation-based methods have shown promising results in image identification. However, they have limitations, such as limited feature extraction that can result in a semantic gap in the image and the need for time-consuming image pre-processing. These limitations directly affect the precision and speed of crop disease diagnosis. On the other hand, deep representation-based methods often utilize deep convolutional neural networks, capable of extracting global features and context from images. However, current research on deep representations primarily focuses on crop disease identification in simple backgrounds. When applied to real-world scenarios, the accuracy of these methods significantly decreases as they cannot efficiently extract local information from complex backgrounds. This makes it challenging for the recognition results to meet the requirements of real-world applications.

In this study, we propose a novel approach to identifying rice diseases that leverages the ResNet-152V2 architecture, a powerful deep learning model, and the attention network mechanism. The attention network mechanism allows the model to focus on relevant areas of the input image, enhancing the precision and effectiveness of disease diagnosis. The intricate design of ResNet-152V2 enables it to extract complex patterns and features from the input data, improving the model’s ability to distinguish between healthy and diseased rice plants. We conducted extensive testing on a large dataset of rice leaf images to evaluate the effectiveness of our proposed method. Our findings indicate that the attention network mechanism, combined with ResNet-152V2, significantly improves the accuracy and efficiency of rice disease detection compared to other approaches. This study contributes to ongoing efforts to develop innovative solutions for plant disease management and precision agriculture.

There is a growing interest in using computer-assisted diagnostics for disease detection and classification, as the traditional method of diagnosing rice leaf diseases is time consuming and challenging. Convolutional Neural Networks (CNNs), a subset of Deep Neural Networks (DNNs), have shown remarkable generalization capabilities in image processing. A recent study demonstrated the potential of CNNs in detecting plant diseases by introducing a Deep Residual Network with attention mechanisms for identifying viruses in tomato leaves [3].

Author [4] proposed the novel concept of the kernel attention mechanism, which is applied to segmenting remote sensing images. Remote-sensing imagery plays a crucial role in monitoring and identifying newly emerging urban areas due to urbanization. To classify rice diseases rather than segment them, this study modifies the kernel attention concept, focusing on extracting the most relevant information.

The following is the Motivation for proposing our research writing over previous studies in this area: -

1. Rice is a vital staple food, but its cultivation faces significant threats from diseases. Traditional manual inspection methods are laborious and prone to errors.

2. Leveraging attention networks in deep learning presents an opportunity to revolutionize disease identification by automating the process and enhancing accuracy, addressing the urgent need for scalable solutions in sustaining rice production and ensuring global food security.

TABLE I. RICE PLANT DISEASES AND REMEDIES

Name of disease	***Bacilli/fungi***	***Contagi-ous part of the plant***	***Symptoms***	***Remedies***
Blast (leaf and collar)	Magnaporthe oryzae	Leaf, collar, parts of panicle, leaf sheath	Lesions or patches with dark green borders that range in colour from white to grey-green.	When applying nitrogen fertilizer, divide it up into two or more applications.
Bacterial blight	Pv. oryzae / Xanthomonas oryzae.	Weeds and stubbles	Turning yellow on the leaves or seedlings withering.	Make use of proportionate quantities of nitrogen and other plant nutrients.
Leaf Scald	Microdochium oryzae.	Wounded leaves, seeds and crop stubbles	In mature leaves, lesions are oblong and have light brown halos. Tips and edges of leaves that glow.	Don't use fertilizer excessively. Use nitrogen in divided doses.
Narrow Brown Spot	Sphaerulina oryzina	Leaves, panicles, sheaths	It's also possible to see brown blemishes on rice plant stems.	Use resistant varieties. Keep fields clean. Use balanced nutrients.
Brown Spot	Pseudomonas cerevisiae pv. cerevisiae	Coleoptile, panicle branches, and glumes	Lesions on sensitive variety measure 5–14 mm in length.	Improve soil fertility. Soak seeds in 53–54°C boiling water for ten to twelve minutes.

II. RELATED WORK

The concept of a classifier using a BP neural network. was presented by the author Libo Liu in order to distinguish between the diseased and healthy portions of rice leaves. Brown spot is the rice disease under consideration here. The findings demonstrate the accuracy with which rice brown spot illnesses may be detected using image analysis and BP neural networks [5]. Neural network techniques for detecting and tracking fruit plant disease from plantation to harvesting were proposed by author M. Jhuria. Total 3 distinct feature vectors were retrieved i.e. morphology, colour, and texture. As opposed to the other two vectors, the morphological characteristics yield 90% of the accurate outcomes [6].

The concept of diagnosing plant diseases with computers was put out by author H. Q. Cap et al in 2018. With a frame rate of 2.0, our approach attained 78% detection performance in the F1-measure [7].

The computer vision approach method was presented by B. S. Ghyar to identify rice crop diseases caused by pests. For the leaf's diseased section, three characteristics were taken off. Utilizing a genetic algorithm, the pertinent traits are chosen. Using the ANN and SVM classification, the accuracy is 92.5% and 87.5%, respectively [8].

In previous studies, Convolutional Neural Networks (CNNs) have demonstrated their efficacy in detecting rice leaf diseases. For instance, a study by Wang [9] introduced a CNN-based approach for rice leaf disease classification, achieving commendable accuracy rates. However, CNNs have inherent limitations in focusing on critical areas or features within an image. To address this issue, recent advancements in deep learning have introduced attention mechanisms. These mechanisms enable models to selectively focus on significant areas or features within an image, thereby enhancing the capacity of model to extract relevant information for disease detection. The kernel attention technique, pioneered by researchers [10] initially applied to the division of images from remote sensing, holds promise in improving CNN performance in image recognition tasks.

Additionally, Residual Networks (ResNets), a class of CNN architectures, have gained popularity for their effectiveness in training very deep networks. The ResNet 152V2 model, a variant of ResNet incorporating architectural enhancements, has shown superior effectiveness in image recognition tasks. In the context of agricultural disease diagnosis, a study by Liu [11] proposed a ResNet 152V2-based method for detecting diseases in tomato leaves. This research provided evidence that ResNet 152V2 is a valuable tool for classifying agricultural diseases. Using the InceptionResNetV2 model, Krishnamoorthy [12] presented a transfer learning strategy in their work. With an identification accuracy of 95.67%, our approach uses weight shaped characteristics along with hyperparameter adjustments to identify three distinct rice illnesses. With a 93.3% accuracy rate, Rahman and colleagues [13] correctly diagnosed rice illnesses by modifying the VGG16 and Inception V3 models. These results demonstrate how deep learning and image processing may be used to identify agricultural diseases with promising results. Wang Chunshan and his team [14] implemented grouped convolution operations, revised the connection approach for residual layers, and constructed a multi-scale residual network. They also developed a multi-scale feature extraction module using resnet18. An accuracy rate of 93.5% was achieved when utilizing self-gathered real-world environmental illness image data. A deep convolution network was used by Qiu and associates [15] to build a model for the identification of rice illness. By adjusting the kernel of convolution widths and pooling functions, they examined the grouping and identification of 3 rice illnesses in order to train this model using the Keras deep learning framework. Over 90% accuracy was attained.

According to the review, the various techniques for detecting plant diseases exhibit several limitations. BP neural networks, as used by Libo Liu, though accurate for detecting brown spot in rice leaves, may lack generalizability across different diseases and crops. M. Jhuria's approach, while effective with morphological features, might be less robust when other feature vectors are less distinguishable. The method by H. Q. Cap et al., despite a 78% detection performance, operates at a low frame rate of 2.0, making it impractical for real-time applications. B. S. Ghyar's approach using genetic algorithms for feature selection, combined with ANN and SVM classifiers, achieved high accuracy but may suffer from computational complexity and inefficiency in feature extraction. CNNs, although effective in studies such as Wang's work on rice leaf disease classification, are inherently limited by their inability to focus on critical image areas without additional mechanisms. The introduction of attention mechanisms helps, but traditional CNNs still face challenges in extracting the most relevant features. Kernel attention techniques and grouped convolution operations, as employed by Wang Chunshan, offer improvements but can be complex and computationally expensive.

III. PROPOSED METHODOLOGY

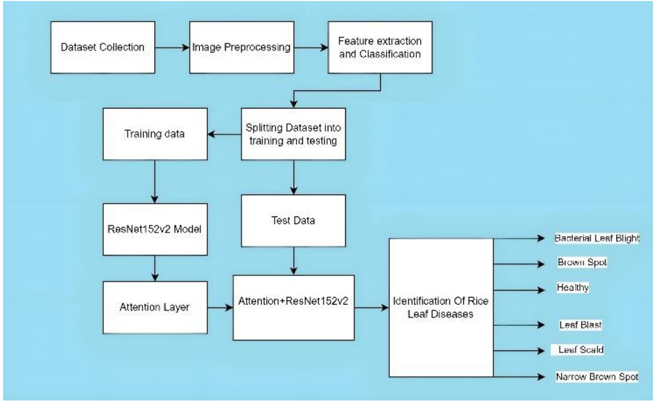

Fig. 1. Block diagram of the proposed work

Fig. 1 represents the workflow of the entire proposed work. The image shows the process of identifying rice leaf diseases using deep learning. The process starts with collecting a dataset of images of rice leaves with different diseases. The images are then preprocessed to remove noise and enhance the features. The features are then extracted from the images using a deep learning model. The features are then used to classify the images into different diseases.

Dataset Collection : A comprehensive dataset for diagnosing rice diseases should encompass a variety of images, including those depicting both healthy rice plants and those afflicted with diseases. It is essential to ensure that this dataset captures a diverse range of conditions and variations reflective of real-world situations. The dataset, comprising a total of 2627 images, is sourced from Kaggle. (Fig.2) illustrates the photos of sample images.

To establish a baseline for healthy plants, collect images of robust rice plants from diverse sources, encompassing agricultural databases, field research, and research facilities. These images will serve as a reference for healthy plants, providing a foundation for comparative analysis.

Incorporate images of rice plants affected by a spectrum of diseases, including but not limited to "Narrow Brown Leaf spot," "Brown spot," "Leaf scald," "Rice blast," "Bacterial blight," and "Rice sheath blight." It is crucial that the dataset represents various stages and severity levels for each disease, offering a comprehensive representation of the different manifestations observed in real-world scenarios.

Fig. 2. Sample images of disease from Plant-village dataset [16]

The provided Fig. 2 showcases a collection of rice leaf samples, each labeled with its corresponding health status or disease type. The samples are organized in a grid format, demonstrating a variety of visual symptoms associated with each disease. Brown spots appear as dark lesions on the leaf surface, while bacterial leaf blight manifests as streaks or patches of discoloration. Narrow brown spots are characterized by elongated, narrow lesions. Leaf scald displays a burnt appearance with dried, brown edges, and leaf blast is indicated by more severe necrosis and decay. Healthy leaves are uniform in color and free of any visible damage or discoloration. This diverse dataset is essential for training and testing machine learning models aimed at accurately diagnosing and distinguishing between different rice leaf diseases.

Data Preprocessing : The subsequent step involves preprocessing the images to ensure uniformity in size and normalization of pixel values. This is crucial to establish consistent input dimensions and pixel value ranges, contributing to enhanced model performance and stability during the training process.

Ensuring uniformity involves setting identical measurements for all images. Standardizing pixel values across photos is achieved by normalizing them to a particular range, such as [0, 1] or [-1, 1]. This normalization process supports in the model's quicker convergence during training. Each image is appropriately labelled based on its category, distinguishing between healthy and diseased plants. The dataset is then partitioned into two distinct sets: training and testing. The testing set serves to calculate the model's ultimate results, while the training set is utilized for model training.

In addition, data augmentation techniques, including scaling, rotating, mirroring, and introducing noise, have been applied to augment the dataset. These techniques contribute to increased diversity within the dataset, facilitating a more robust training process.

Feature extraction and Classification : In the feature extraction phase, we identify traits that serve as distinguishing characteristics, such as color, texture, and shape, to differentiate healthy from unhealthy sections in rice plant images. These features are extracted from segmented regions of the images, resulting in feature vectors that represent each area. These feature vectors become inputs for models of machine learning, such as support vector machines or neural networks, enabling the classification of regions as either healthy or diseased. For supervised classification, the crucial step involves gathering known pixels, which are utilized to train the classifier. This trained classifier can then accurately classify different images based on the learned traits. On the other hand, unsupervised classification, specifically clustering, groups pixels based on their intrinsic characteristics, eliminating the need for pre-existing labeled data. The user determines the number of clusters or groups formed during this process. Unsupervised classification becomes particularly valuable in scenarios where labeled pixels are unavailable, offering a flexible approach to categorizing image content based on inherent similarities.

Model Architecture: In identifying the illness in the rice crop we use the Resnet152V2 model as the base model for the classification task with the attention mechanism (channel wise attention) integrated in it using the transfer learning technique. The main motive of integration of the attention mechanism is made the model to focus on the most relevant features of the images for making precise predictions. The fully connected layers at the top of the network have been left out, and the model is initialized using pre-trained weights from ImageNet. This enables the model to utilize the knowledge learned from the ImageNet dataset, customizing it for the intended use of rice leaf disease classification.

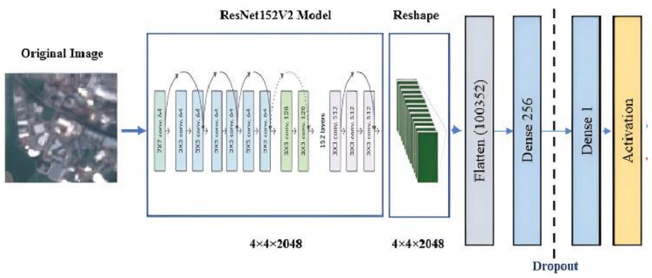

Fig. 3. ResNet 152v2 Model Architecture [17]

Fig. 3 illustrates the workflow of the ResNet152V2 model for image recognition. Starting with the original image, it passes through multiple convolutional layers of the ResNet152V2 architecture, is reshaped, flattened, and then processed through dense layers with dropout regularization, culminating in an activation function to produce the final output.

- **Fine Tuning**: In this stage, the ResNet152V2 architecture is employed as the base model for rice leaf disease classification. The uppermost layers of the network that are fully connected are excluded, and model initialization is achieved by using weights that have been pre-trained from ImageNet. To prevent updates to the weights in the initial layers, freezing is applied up to the conv5_block1_preact_bn layer. Subsequently, the layers following this block are set to be trainable, helping the final convolutional layers to be fine-tuned. This strategic approach allows the model to adapt its pre-learned knowledge from ImageNet to the specific task of rice leaf disease classification.

- **Attention Mechanism**: The next step involves enhancing the model with a channel-wise attention mechanism. This mechanism comprises a GlobalAveragePooling2D layer, a softmax activated Dense layer to generate attention likelihoods, and a multiplication operation with the output of the GlobalAveragePooling2D layer. This addition empowers the model to selectively focus on the most pertinent features during predictions, enhancing its ability to identify and classify rice leaf diseases effectively.

- **Fully Connected Layers**: Following the attention mechanism, fully connected layers are introduced to further refine the model's features. An activation of ReLU and a Dense layer containing 256 units are added, followed by an output layer containing the quantity of units corresponding to the distinct output groups as well as a softmax activation mechanism. These fully connected layers contribute to the final stages of feature extraction and classification, completing the comprehensive architecture designed for accurate rice leaf disease identification.

- **Model Compilation and Model Training**: The accuracy metric, categorized cross-entropy loss function, and Adam optimizer are utilized to create the model. Training is conducted on the designated training set, and performance is evaluated on the validation set. Hyperparameter adjustments can be made based on the model's efficiency during training.

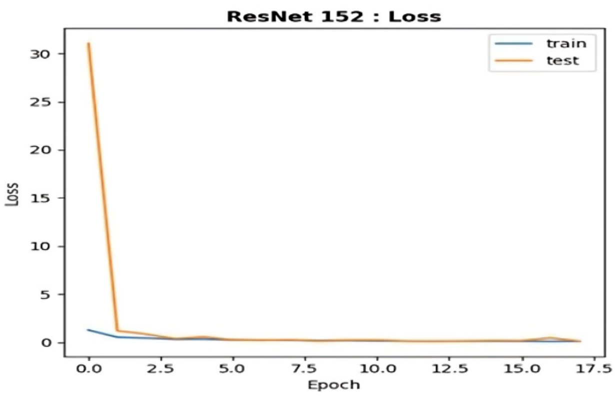

Fig. 4. Loss curve for ResNet 152v2 Model

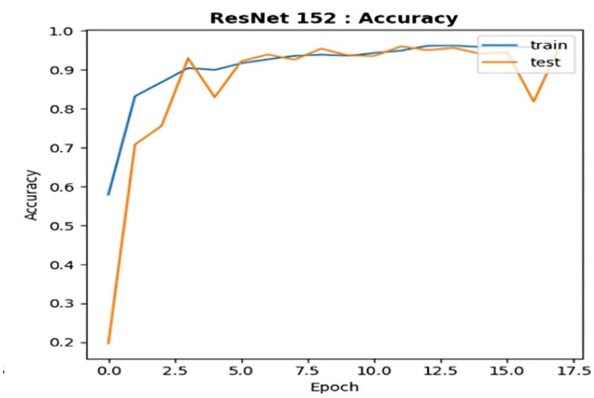

Fig. 5. Accuracy curve for ResNet 152v2 Model

Fig. 4 and Fig. 5 illustrates the loss and accuracy curves for both training and testing datasets over 18 epochs using the ResNet 152V2 model respectively. A sharp decline in loss is observed in the initial epochs, stabilizing near zero, indicating effective learning and minimal overfitting throughout the training process. Initially, accuracy rapidly increases for both datasets, with the training accuracy slightly outperforming the testing accuracy throughout the epochs. The model achieves high accuracy, demonstrating effective learning and generalization.

IV. RESULTS AND DISCUSSION

The performance of the ResNet-152v2 architecture in identifying rice leaf diseases can be assessed using various metrics. The study's evaluation criteria, such as the F1 score, precision, accuracy and recall, are aligned with the research goals and key areas of interest. The precision, recall, accuracy and F1 score were computed using specific evaluation matrices to gauge the model's effectiveness.

Recall Value: The percentage of accurately identified positive samples to actual positive samples is known as the recall rate. The formula is given as follows in equation (1).

$$Recall = \frac{TP}{TP+FN} \quad (1)$$

Precision Value: Precision is defined as the ratio of the number of positive samples classified correctly to the total number of positive samples produced by the classifier as illustrated in equation (2).

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

F-1 value: It refers to the harmonic average of precision rate and recall rate as illustrated in equation (3).

$$F1 - Score = 2 \times \frac{(Precision \times Recall)}{(Precision + Recall)} \quad (3)$$

Subsequently, the model's effectiveness is assessed on the testing set. To gauge its effectiveness, the results are compared with those of other state-of-the-art models, including VGG16, VGG19, AlexNet, and ResNet50. Remarkably, our ResNet152V2 model outperforms these counterparts, demonstrating superior accuracy in rice leaf disease classification (see table 2).

TABLE II. MODEL PERFORMANCE METRICS

Models	*Accuracy*	*Precision*	*Recall*	*F1-Score*
ResNet50	0.447	0.377	0.447	0.393
Vgg19	0.273	0.18	0.27	0.212
Vgg16	0.167	0.027	0.167	0.0476
AlexNet	0.313	0.289	0.312	0.265
ResNet152v2	0.964	0.9644	0.964	0.9633

This comprehensive evaluation establishes our model's effectiveness and positions it as a robust solution for accurate and reliable identification of rice leaf diseases.

In this research, we introduced a unique attention network on the ResNet152V2 architecture for rice disease classification, featuring a channel attention mechanism strategically focus on key aspects for disease identification Our experimental results demonstrated the usefulness of the attention-based strategy in direct the model, achieving test set accuracy of 96.40%, outperforming state-of-the-art models. The attention mechanism let the model concentrate on the greatest number of features, resulting in improved accuracy and robustness. The model's high test set accuracy highlights the potential of AI to be widely used in agricultural disease diagnosis, potentially reducing financial losses for farmers and improving crop yields.

Fig. 6. Accuracy Value Graph

Fig. 7. Precision Value Graph

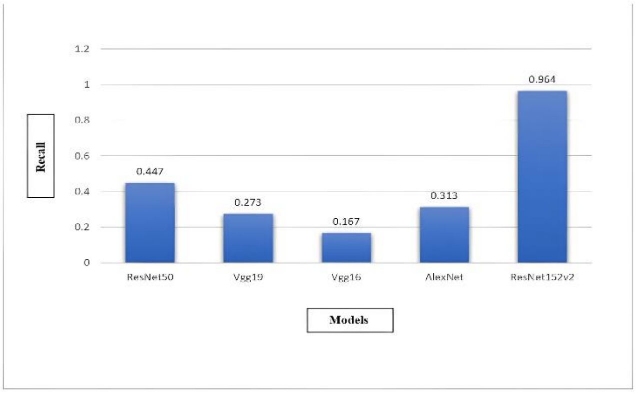

Fig. 8. Recall Value Graph

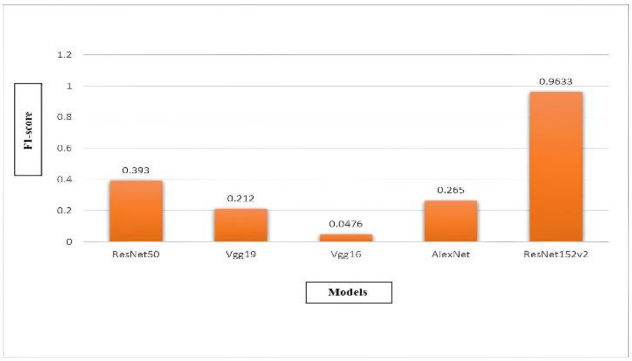

Fig. 9. F1-score Value Graph

The suggested approach can serve as a standard for upcoming research on rice disease classifica-tion and can be adapted to other plant disease classification tasks. The results of this study have significant implications for agricultural disease management, enabling accurate AI-assisted diagnosis and improving crop yields. The attention mechanism used in this study is a simple yet effective way to allow the model to concentrate on the most important aspects, making it a promising approach for rice disease classification. Overall, this research paper in-dicates a novel and effective solution for rice disease classification, contributing to the devel-opment of AI-assisted agricultural disease management. The system utilized for training this model should have a minimum of 12 GB of RAM and 128 GB of storage. Figures 6, 7, 8 and 9 depict the accuracy, precision, recall value, and F1-score of various models, respectively. These figures graphically represent the data presented in Table 2.

TABLE III. COMPARISON TABLE OF RESNET152v2, RESNET50, VGG16, VGG19, ALEXNET

Sensitivity score of various models	*Bacterial Leaf Blight*	*Brown Spot*	*Healthy*	*Leaf Blast*	*Leaf Scald*	*Narrow Brown Spot*
ResNet 152v2	0.989	0.8409	0.997	0.966	0.989	0.988
ResNet50	0.443	0.189	0.761	0.238	0.556	0.682
VGG16	0.001	0.043	0.001	0.112	0.098	0.054
VGG19	0.132	0.213	0.254	0.287	0.318	0.264
AlexNet	0.43	0.387	0.476	0.298	0.416	0.216

Table 3 represents the sensitivity scores of five models- ResNet152v2, ResNet50, Vgg16, Vgg19, and AlexNet -in identifying six rice leaf diseases: Bacterial Leaf Blight, Brown Spot, Healthy, Leaf Blast, Leaf Scald, and Narrow Brown Spot. ResNet152v2 consistently shows the highest sensitivity across all diseases, whereas Vgg16 often has the lowest sensitivity.

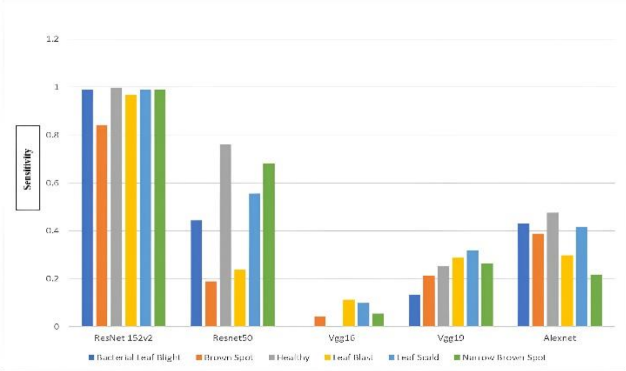

Fig. 10. Sensitivity of Various Models for Different Leaf Diseases

Fig. 10 provides a graphical representation of the data presented in Table 3.

V. CONCLUSION

In conclusion, since quick and precise detection of rice diseases is essential to averting huge financial losses for farmers and increasing crop yields, our work has important implications for agricultural disease management. The suggested model can function as a foundation for further studies on rice disease classification and may be modified for use in other activities involving the classification of plant diseases. This study's attention mechanism is a straight-forward yet efficient technique to let the model concentrate on the most important characteristics, which makes it a potential method for diagnosing agricultural diseases. In the future, this project will enable us to identify and mitigate diseases using advanced technologies, ultimately reducing crop wastage and facilitating the production of high-quality rice.

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