Rice Leaf Disease Detection Using Deep Learning Models

A Project Submitted in fulfillment of the requirements for the award of the degree of

Bachelor of Technology

Submitted by

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Candidate's Declaration

We hereby declare that the research presented in this dissertation titled " **Rice Leaf Disease Detection Using Deep Learning Models**" In fulfillment of the requirements for the award of the degree of **Bachelor of Technology** and submitted in the Department of Computer Science and Engineering of the National Institute of Technology Hamirpur, is an authentic record of our work carried out during a period from July 2023 to May 2024 under the guidance of **Dr. Mohit Kumar**, Assistant Professor, Department of Computer Science and Engineering, National Institute of Technology Hamirpur.

The matter presented in this report has not been submitted by us for the award of any other degree of this or any other Institute/University.

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This is to certify that the above statement made by the candidates is true to the best of my knowledge and belief.

Date:

Dr. Mohit Kumar
(**Assistant Professor**)

DBPC Convener **- HOD CSE**

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ABSTRACT

With the global population rising, ensuring there's enough food for everyone becomes crucial. Rice, a staple for many, is under threat from various diseases that can harm crop yield. Detecting these diseases early is key to preventing widespread crop losses and ensuring there's enough food for everyone. However, traditional methods of disease detection, like visual inspections, are often difficult and expensive, especially in developing countries.

To tackle this challenge, this project introduces a new way of using computers to detect rice leaf diseases quickly and affordably. We use four different lightweight neural networks: MobileNet V2, Efficient Net B0, Inception V3, and SVM with ORB features, to make our method efficient and accurate.

Key contributions include creating the Dhan-Shomadhan dataset, which contains images of five harmful rice leaf diseases. We also use advanced neural network architectures like MobileNet V2, Efficient Net B0, and Inception V3, known for their efficiency and accuracy. Additionally, we explore classical machine learning techniques like SVM with ORB features, making our approach versatile and effective.

These experiments show that EfficientNet B0 performs well in detecting rice leaf diseases, competing with the best mobile networks available. Although training the model can be complex, we aim to simplify this in the future, making it easier to use on portable devices. This could revolutionize rice disease detection, making it automated and accessible to all.

CONTENTS

LIST OF ACRONYMS / ABBREVIATIONS

LR: Logistic Regression

NLP: Natural Language Processing

KNN: K Nearest Neighbours

SVM: Support Vector Machine

DNN: Deep Neural Networks

NB: Naive Bayes

ANN: Artificial neural networks

SVC: Support Vector Classifier

ReLU:Rectified Linear Unit

Chapter 1
Introduction

1.1 Overview

Rice, as a fundamental staple food, plays a crucial role in sustaining the world's population. It is particularly significant in Asian countries, where it is a dietary staple for millions. However, the global production of rice faces significant threats from various plant diseases that can adversely affect crop yields, posing a potential risk to food security. This project explores the application of deep learning-based Convolutional Neural Networks (CNNs) to enhance the identification of rice plant diseases, leveraging advanced techniques such as transfer learning and attention mechanisms. By developing a robust and automated system for the early and accurate detection of rice plant diseases, this project aims to contribute to the preservation of agricultural yields and ensure global food security.

1.2 Current Challenges

The susceptibility of rice plants to various diseases presents a significant challenge to agricultural productivity and food security. The key challenges and issues include:

1.Variety of Diseases:

- Rice plants are prone to a wide range of diseases such as bacterial blight, rice blast, sheath blight, and viral diseases.
- Each disease affects different parts of the plant and can lead to significant yield losses if not managed properly.

2.Traditional Detection Methods:

- Reliance on Visual Observations:

  1. Farmers and agricultural workers typically rely on visual inspections to identify symptoms of disease.

2. These inspections require considerable expertise and experience to accurately diagnose the disease.

- Labor-Intensive:

1. The process of manually inspecting fields is time-consuming and labor-intensive.

2. Large-scale rice farms require significant manpower to conduct thorough inspections.

- Prone to Inaccuracies:

1. Visual inspection methods are subjective and can lead to misdiagnosis due to human error.

2. Early-stage symptoms are often subtle and easily overlooked, leading to delayed interventions.

3. Limited Access to Specialists:

1.In many regions, especially in developing countries, there is a shortage of plant disease specialists.

2.Farmers in remote or rural areas often do not have access to expert advice, making disease management more difficult.

4. Increasing Global Population:

- The global population is projected to continue growing, leading to increased demand for staple foods like rice.
- Ensuring food security becomes more challenging as more rice needs to be produced on the same or less agricultural land.

5. Impact on Food Security:

- Diseases in rice crops can lead to substantial yield losses, directly affecting food availability.
- Reduced rice yields can lead to higher food prices, impacting the economic stability of communities reliant on rice as a staple food.

6.Need for Efficient Solutions:

- There is a pressing need for more efficient, accurate, and scalable solutions to detect and manage rice plant diseases.
- Technological advancements, such as automated detection systems using machine learning and computer vision, offer promising solutions.
- These advanced systems can provide timely and precise disease identification, enabling farmers to take early and effective action to protect their crops.

This detailed breakdown highlights the key challenges and emphasizes the need for improved methods to detect and manage rice plant diseases to sustain crop yields and ensure global food security.

1.3 Proposed Solution

This project proposes the use of deep learning-based Convolutional Neural Networks (CNNs) to automate the identification of rice plant diseases. The goal is to develop a robust, efficient, and scalable system for early and accurate disease detection, thereby enhancing agricultural productivity and food security. The project evaluates several advanced models, each offering unique strengths in terms of accuracy and computational efficiency:

MobileNet V2

- **Lightweight Design**: **MobileNet V2** is designed to be lightweight and efficient, making it suitable for deployment on mobile and embedded systems where computational resources are limited.
- **Performance**:In our experiments, MobileNet V2 achieved an accuracy of 91%. This demonstrates its capability to handle image classification tasks effectively while maintaining a balance between performance and resource consumption.
- **Advantages**:The efficiency of MobileNet V2 makes it particularly useful for real-time applications in the field, where quick and accurate disease detection is crucial.

EfficientNet B0

- **Scalable Architecture**: EfficientNet B0 belongs to the EfficientNet family, known for its ability to scale up in depth, width, and resolution while maintaining a balance between accuracy and computational efficiency.
- **Performance**:Our experiments with EfficientNet B0 yielded a remarkable accuracy of 99.82%, showcasing its superior performance in image recognition tasks.
- **Advantages**:The model's ability to achieve high accuracy with fewer parameters compared to traditional deep learning models makes it ideal for practical applications in agricultural settings, where computational resources might be constrained.

Inception V3

- **Renowned for Image Recognition**:Inception V3 is well-known for its high performance in image recognition tasks. It utilizes inception modules to improve feature extraction and model efficiency.
- **Performance**:The model achieved an accuracy of 91.36% in our experiments, demonstrating its effectiveness in identifying rice plant diseases.
- **Advantages**:Inception V3's sophisticated architecture allows it to handle complex image classification tasks, making it a reliable choice for disease detection.

SVM with ORB Features

- **Combination of Traditional and Modern Techniques**:This approach combines a Support Vector Machine (SVM) with Oriented FAST and Rotated BRIEF (ORB) features for feature extraction and classification.
- **Performance**:Despite its simplicity, this method achieved a respectable accuracy of 67%. It highlights the potential of integrating classical machine learning techniques with modern feature extraction methods.
- **Advantages**:The use of SVM with ORB features provides a simpler and computationally less intensive alternative, which can be useful in settings with limited computational resources.

Experimental Setup and Optimization

- **Rigorous Exploration**: Our experiments involved a thorough exploration of various hyperparameters and optimization strategies. These included variations in optimizer types, learning rates, batch sizes, epochs, and dropout rates.

- **Optimal Configurations**: Through meticulous experimentation, we identified the optimal configurations for each model. This process ensured that each model performed at its best under different conditions.

Proposed Solution

- **Deep Learning Techniques**:The project leverages advanced deep learning techniques to enhance the early and accurate detection of rice plant diseases. This includes the use of CNNs for feature extraction and classification, and the incorporation of transfer learning and attention mechanisms to improve model performance.

Benefits:

- The automated detection system developed through this project can significantly reduce the reliance on manual inspection methods, thereby saving time and resources.
- Early and accurate disease detection enables timely interventions, which can mitigate the impact of diseases on crop yields and contribute to sustainable agricultural practices.
- By improving the efficiency and accuracy of disease detection, the project supports food security efforts and helps ensure a stable food supply.

Conclusion

- **Overall Impact**:The project's findings and methodologies hold significant implications for the agricultural sector. They offer a transformative solution for enhancing disease detection in rice plants, thereby improving agricultural productivity and food security.
- The integration of deep learning and computer vision technologies into agricultural practices represents a significant advancement in the field of automated disease identification.

This detailed description provides a comprehensive understanding of the project's scope, methodologies, and potential impact on agricultural practices and food security.

1.4 Structure of Project Report

The structure of this project report is organized into five chapters:

- **Chapter 3: Motivation-** This chapter explains the foundational concepts used in developing the proposed model.
- **Chapter 4: Methodology**- This chapter describes the proposed model, the training dataset, and the evaluation metrics.
- **Chapter 6: Results and analysis -** This chapter presents the generated results, a comparison of the proposed work with state-of-the-art methods, and showcases generated captions with images.
- **Chapter 7: Conclusion and Future Work**- This chapter provides the conclusion of the study and discusses potential avenues for future research.

Chapter 2

Literature Review

2.1 Overview of previous studies

The previous study focuses on attention mechanisms and localization techniques, shedding light on important plants for disease detection globally. The review process follows a systematic approach, covering methods based on Image Processing (IP), Machine Learning (ML), and Deep Learning (DL) techniques. The research questions addressed in the paper include data collection methods, availability of datasets, performance evaluation measures, and the contribution of traditional IP and ML methods to plant disease detection.

The previous study discusses the selection criteria, quality assessment criteria, and the process of filtering and selecting research articles. It highlights the data extraction process, where 148 research articles published between 2005 and 2022 were selected for review. These articles utilize IP, ML, DL, and other techniques for plant disease detection. The results and discussion section presents the contributions of researchers, qualitative and quantitative analyses, and the focus on IP, ML, and DL methods. The paper delves into data collection methods, preprocessing strategies, publicly available datasets, and performance evaluation metrics used in plant disease detection research.

Furthermore, the paper explores how traditional IP and ML methods have evolved in addressing plant disease detection challenges. It discusses the use of various algorithms like Support Vector Machine (SVM), Artificial Neural Network (ANN), Naive Bayes (NB), and clustering techniques in disease detection models. The research paper provides insights into the advancements in vision-based machine learning techniques for plant disease identification, offering a detailed account of the methodologies, datasets, and evaluation metrics used in this field.

2.2 Literature Survey

LIERATURE SURVEY

S.no	Title Of Paper	Author Name	Year	Focus of Paper	Advantage	Disadvantage	Type
1.	Trends in vision-based machine learning techniques for plant disease identification	Poornima Singh Thakur, Pritee Khanna, Tanuja Sheorey, Aparajita Ojha	2022	Examines and discusses machine learning techniques	Lightweight CNN, transfer learning, autoencoders, and GANs are explored for high-performance models	Deep CNN models lack testing on in-field datasets	Journal
2.	A Systematic Review of Recent Machine Learning Techniques for Plant Disease Identification and Classification	Lavika Goel & Jyoti Nagpal	2023	Pointing out Support Vector Machine (SVM) as extensively employed for disease classification.	ORB features with Linear SVM (99.98%), GLCM plus MobileNet (99.62%), and GLCM plus InceptionV3 (99.74%), demonstrate high accuracy rates in disease classification.	Requiring distinct samples under various environmental conditions. Obtaining and managing such extensive datasets can be challenging.	Journal

S.no	Title Of Paper	Author Name	Year	Focus of Paper	Advantage	Disadvantage	Type
3.	Rice leaf disease detection based on bidirectional feature attention pyramid network with YOLO v5 model	V Senthil Kumar,M Jaganathan,A Viswanathan,M Umamaheswari,J Vignesh	2023	The article proposes a Multi-scale YOLO v5 detection network, leveraging DenseNet-201 as the backbone network and Bidirectional Feature Attention Pyramid Network for feature extraction.	The proposed DenseNet-Bi-FAPN with YOLO v5 demonstrates superior accuracy (94.87%) compared to existing methods	The dataset lacks diversity or does not adequately cover real-world scenarios, the model's generalization may be limited.	Journal
4.	Rice Disease Detection Using Deep Learning VGG-16 Model and Flask	Bhairu Jangid, As. Prof. R.S. Sharma Rajasthan Technical University, Kota	2023	The application aims to utilize Convolutional Neural Network (CNN) technology, specifically the VGG-16 model, for the classification of diseases	The model achieves a high accuracy rate of 90%	There's no detailed discussion on other evaluation metrics (precision, recall, F1 score), There's no explicit comparison with other neural network models	Journal
5.	Identification of rice plant diseases using lightweight attention networks	Junde Chen, Defu Zhang, Adnan Zeb,Yaser A. Nanehkaran	2021	Using MobileNet-V2 pre-trained on ImageNet as the backbone network	High Accuracy,Diverse Dataset	specific performance metrics (precision, recall, F1 score) are not provided	Journal

S.no	Title Of Paper	Author Name	Year	Focus of Paper	Advantage	Disadvantage	Type
6.	Deep Learning for Rice Leaf Disease Detection in Smart Agriculture	Nguyen Thai-Nghe, Ngo Thanh Tri, and Nguyen Huu Hoa	2022	Detecting rice leaf diseases using deep learning (EfficientNet) on mobile devices	Achieves an average precision of over 95%, The mobile application can rapidly detect about 1.7 seconds	Data Limitation, Model focuses on three common rice leaf diseases	Journal
7.	Disease Detection on Rice Leaves through Deep Learning with InceptionV3 Method	Aria Maulana, Muhammad Rivaldi Asyhari, Yufis Azhar, Vinna Rahmayanti, Setyaning Nastiti	2023	The research's objective, which is to prevent the spread of rice diseases through a deep learning approach, specifically using the InceptionV3 method	The InceptionV3 model achieved an impressive average accuracy of 97.47%	The relatively small size of the dataset	Journal

Chapter 3

Motivation

The motivation for this project stems from the critical need to address the challenges posed by rice leaf diseases, which significantly impact agricultural productivity and food security. Several key factors drive the necessity for this research:

1. Prevalence of Rice Diseases: - Rice, being a staple food for a large portion of the global population, is highly susceptible to various diseases such as bacterial blight, rice blast, and sheath blight. These diseases can severely reduce crop yields and affect food supply.

2. Limitations of Traditional Methods: - Traditional methods of disease detection rely heavily on visual inspections conducted by farmers or agricultural workers. These methods are labor-intensive, time-consuming, and prone to inaccuracies, especially in regions with limited access to plant disease specialists.

3. Technological Advancements in Deep Learning:- The rapid advancements in deep learning and computer vision technologies offer new opportunities to automate and enhance the accuracy of disease detection. Research has shown that models such as EfficientNet and InceptionV3 can achieve high precision and accuracy in identifying rice leaf diseases.

- For instance, Nguyen Thai-Nghe et al. (2022) demonstrated that the EfficientNet model can achieve an average precision of over 95% and rapidly detect diseases in approximately 1.7 seconds.

- Similarly, Aria Maulana et al. (2023) showed that the InceptionV3 model could achieve an impressive accuracy of 97.47%.

4. Need for Scalable Solutions:- Given the increasing global population, the demand for rice is expected to rise, necessitating scalable solutions that can efficiently manage and mitigate the impact of diseases on rice crops. Automated detection systems powered by deep learning can provide timely and precise disease identification, enabling early intervention and reducing crop losses.

5. Enhancing Agricultural Practices: - By integrating deep learning-based disease detection into agricultural practices, farmers can benefit from early and accurate diagnosis, leading to more effective and targeted interventions. This can significantly enhance crop management, optimize resource use, and improve overall agricultural sustainability.

6. Contributing to Food Security: - The successful implementation of automated disease detection systems can play a vital role in ensuring food security. By minimizing the impact of diseases on rice crops, these systems can help stabilize food supply and support the livelihoods of millions of people who depend on rice as a staple food.

7. Research and Development:- The findings from this project can serve as a foundation for further research and development in the field of automated disease identification in crops. The insights gained can inspire new methodologies and innovations aimed at addressing agricultural challenges across various contexts.

Conclusion

The motivation for this project is deeply rooted in the urgent need to improve rice disease management through advanced technological solutions. By leveraging deep learning models such as EfficientNet and InceptionV3, this project aims to develop a robust, accurate, and scalable system for the early detection of rice plant diseases, ultimately contributing to sustainable agricultural practices and global food security.

Chapter 4

Methodology

4.1 Used Models

Model 1: MobileNet V2

Overview: MobileNet V2 is a lightweight CNN architecture optimized for mobile and embedded applications, using depthwise separable convolutions to reduce computational costs while maintaining accuracy.

Steps:

```
MobileNetV2 Model

Input (224x224x3)

|

|-- Convolutional Layer (32 filters)

|-- ReLU Activation

|-- Inverted Residual Blocks (19 layers)

|-- Each block consists of:

|     |-- Convolutional Layer (64 filters)

|     |-- ReLU Activation

|     |-- Convolutional Layer (64 filters)

|     |-- ReLU Activation

|-- Global Average Pooling Layer

|-- Dense Layer (50 neurons, Softmax Activation)
```

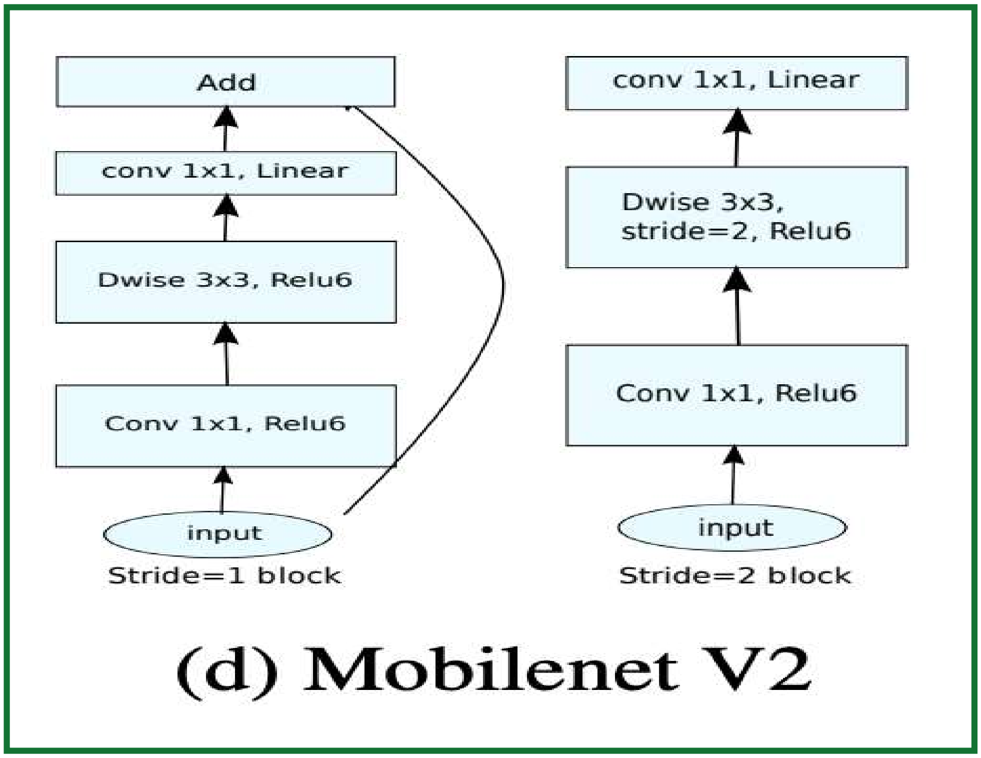
|-- Output Layer (5 classes)

Model Summary:

- Lightweight and efficient for mobile use.
- Achieved 91% accuracy in experiments.

code:-

```
grid_search = GridSearchCV(estimator=keras_model, param_grid=param_grid, cv=3, verb
grid_result = grid_search.fit(train_validation_generator)
print("Best Parameters:", grid_result.best_params_)
print("Best Accuracy:", grid_result.best_score_)
test_accuracies = []
for model in grid_result.cv_results_['params']:
    keras_model = tf.keras.wrappers.scikit_learn.KerasClassifier(
        build_fn=create_model,
        input_shape=(224, 224, 3),
        num_classes=5,
        verbose=0,
        **model
    )
    keras_model.fit(train_validation_generator)
    test_accuracy = keras_model.score(test_generator)
    test_accuracies.append(test_accuracy)
best_model_index = np.argmax(test_accuracies)
best_model_params = grid_result.cv_results_['params'][best_model_index]

print("Best Model Parameters based on Test Accuracy:", best_model_params)
print("Test Accuracy of Best Model:", test_accuracies[best_model_index])
```



Model 2: EfficientNet B0

Overview:EfficientNet B0 is designed for high accuracy with fewer parameters and computations, using compound scaling to balance depth, width, and resolution.

Steps:

1. **Stem Layer:**
   - Initial processing of the input image.
2. **Blocks:**
   - Seven blocks, each with multiple sub-blocks.
   - Sub-blocks use MBConv with a 3x3 kernel.
   - Includes depth wise separable convolutions, batch normalization, and swish activation.
   - Squeeze and excitation optimization recalibrates feature maps.
3. **Project Layer:**
   - Final layer in each sub-block uses 1x1 convolution.
4. **Final Layers:**
   - After the blocks, common final layers are applied.
   - Batch normalization and swish activation.

○ Global average pooling.

○ Dense layer with softmax activation.

Model Summary:

- Balanced scaling of depth, width, and resolution.
- Achieved 99.82% accuracy.
- Efficient and high-performing.

Code:

```
        for batch_size in batch_sizes:
            for epochs in num_epochs:
                for dropout_rate in dropout_rates:

                    units_fc = random.choice([64, 128, 256, 512, 1024])

                    print(f"\nTraining with optimizer={optimizer}, learning_rate={learning_rate}


                    hist = train_model(train_x, train_y, optimizer, learning_rate, batch_size, e
                    accuracy = hist.history['accuracy'][-1]
                    print(f"Accuracy: {accuracy}")


                    if accuracy > best_accuracy:
                        best_accuracy = accuracy
                        best_hyperparameters = {
                            'optimizer': optimizer,
                            'learning_rate': learning_rate,
                            'batch_size': batch_size,
                            'epochs': epochs,
                            'dropout_rate': dropout_rate,
                            'units_fc': units_fc
                        }
```

Model 3: Inception V3

Overview:Inception V3 uses inception modules with parallel convolutions of different sizes to capture features at multiple scales.

Steps:

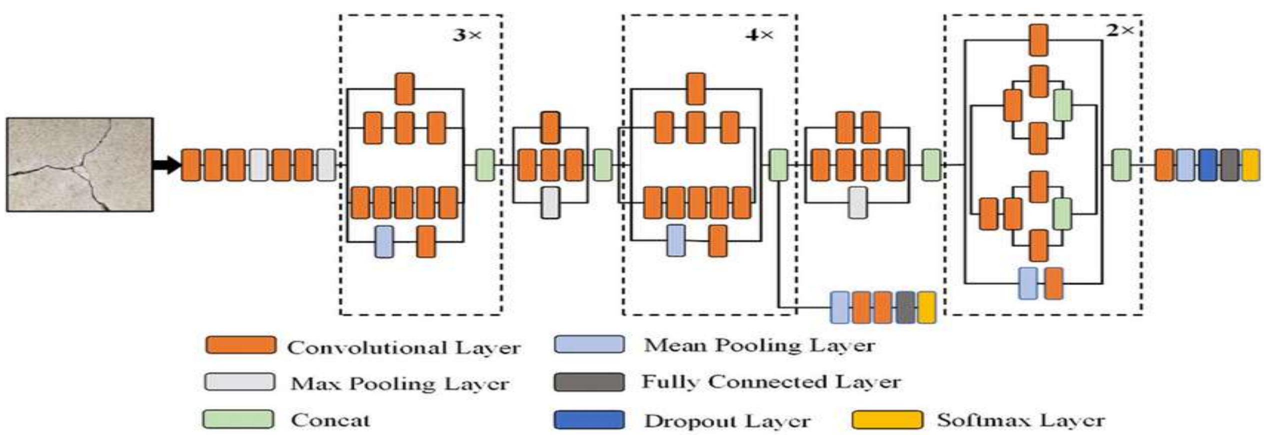
1. **Input Layer:**
   - Input image size: 299x299.
2. **Initial Convolutional Layers:**
   - Series of convolutional layers with varying filter sizes.
   - Max pooling and batch normalization.
3. **Inception Modules:**
   - Parallel convolutions with different filter sizes (1x1, 3x3, 5x5).
   - Factorized convolutional to reduce parameters.
   - Auxiliary classifiers for improved gradient flow.
4. **Pooling Layers:**
   - Max pooling and average pooling for dimensionality reduction.
5. **Fully Connected Layers:**
   - Dense layers for final feature aggregation.
6. **Output Layer:**
   - Softmax layer for classification output.

Model Summary:

- Captures diverse features with parallel convolutions.
- Achieved 91.36% accuracy.
- Effective for image recognition tasks.

Code

```
    model.fit(train_generator,
              steps_per_epoch=train_generator.samples // batch_size,
              epochs=epochs,
              validation_data=test_generator,
              validation_steps=test_generator.samples // batch_size,
              verbose=0)

    test_loss, test_acc = model.evaluate(test_generator, steps=test_generator.samples // batch_s

    combination_name = f"LR={lr}, Epochs={epochs}, Optimizer={optimizer}, Reg={reg}"
    accuracy_per_combination[combination_name] = test_acc

    if test_acc > best_accuracy:
        best_accuracy = test_acc
        best_hyperparameters = (lr, epochs, optimizer, reg)
        best_model = model

for combination_name, accuracy in accuracy_per_combination.items():
    print(f"Combination: {combination_name}, Accuracy: {accuracy}")

print("\nBest Hyperparameters:")
print("Learning Rate:", best_hyperparameters[0])
print("Epochs:", best_hyperparameters[1])
print("Optimizer:", best_hyperparameters[2])
print("Regularizer:", best_hyperparameters[3])
```



Model 4: SVM with ORB Features

Overview:Combines Support Vector Machines (SVMs) with ORB (Oriented FAST and Rotated BRIEF) features for efficient image classification.

Steps:

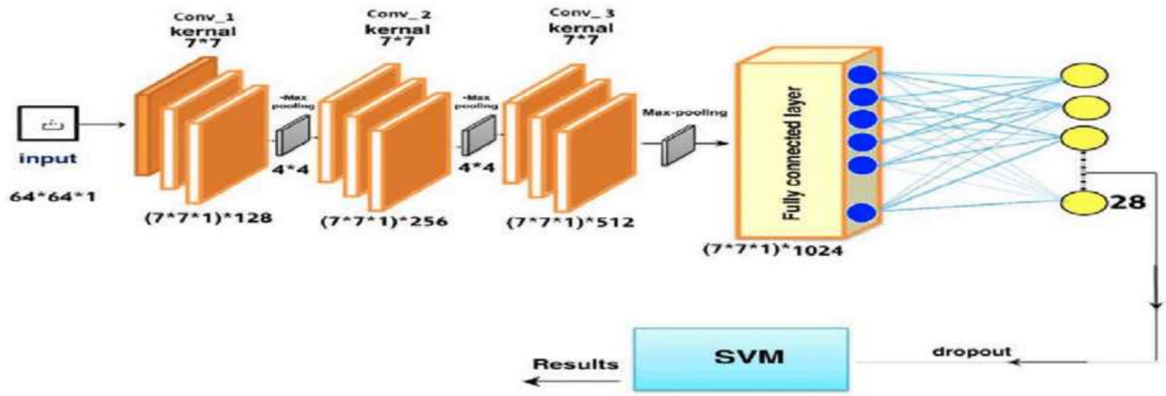
1. **Image Preprocessing:**
    - Resize and normalize the input image.
2. **ORB Feature Extraction:**
    - Extract keypoints using FAST.
    - Compute binary descriptors using BRIEF.
3. **Feature Normalization:**
    - Normalize ORB features to a common scale.
4. **SVM Training:**
    - Train SVM on a labeled dataset with ORB features.
    - Optimize the hyperplane to separate classes.
5. **SVM Classification:**
    - Classify new images based on ORB features.

Model Summary:

- Combines traditional machine learning with modern feature extraction.
- Achieved 67% accuracy.
- Lightweight and suitable for real-time applications.

Code

```
label_encoder = LabelEncoder()
label_encoder.fit(labels)
labels_encoded = label_encoder.transform(labels)


train_features, test_features, train_labels, test_labels = train_test_split(features, labels_encoded, test_size=0.2, random_state=42)


scaler = StandardScaler()
train_features_scaled = scaler.fit_transform(train_features)
test_features_scaled = scaler.transform(test_features)


param_grid = {'C': [1, 10, 100, 1000], 'kernel': ['linear', 'rbf'], 'gamma': ['scale', 'auto']}
grid_search = GridSearchCV(SVC(), param_grid, cv=5)
grid_search.fit(train_features_scaled, train_labels)


best_svm_model = grid_search.best_estimator_


print("Best Parameters:")
print(best_svm_model.get_params())
```



Overall Methodology:

1. **Data Collection and Preprocessing:**
    - Gather a dataset of rice leaf images with various diseases.
    - Preprocess images (resizing, normalization).
2. **Model Training:**
    - Train each model (MobileNet V2, EfficientNet B0, Inception V3, SVM with ORB) on the dataset.
    - Fine-tune hyperparameters (learning rate, batch size, epochs).
3. **Model Evaluation:**
    - Evaluate models on a validation set.
    - Compare accuracy, efficiency, and computational cost.
4. **Optimization:**
    - Identify the best-performing model.
    - Optimize for deployment (e.g., on mobile devices).
5. **Deployment:**
    - Deploy the model for real-time disease detection.
    - Implement an application for use by farmers.

By following these methodologies, the project aims to develop a robust and efficient system for the early detection of rice leaf diseases, leveraging advanced deep learning techniques to support sustainable agriculture and improve food security.

4.2 Dataset and Training

4.2.1 Dataset

The dataset used is very important when it comes to the training of a machine learning model. Since the machine learning model has more layers and is used to perform training where we have a large amount of data available we want much more accurate results. Therefore, the dataset used influences the working of the model to a very large extent. It consists of the already existing data (labeled or unlabelled) for any kind of model.The dataset we used was Dhan-Shomadhan: A Dataset of Rice Leaf Disease Classification for Bangladeshi Local Rice - Mendeley Data has a total of 5 different harmful diseases of rice leaf called Brown Spot, Leaf Scaled, Rice Blast, Rice Turngo, Sheath Blight and it contains 1106 picture in two different background variation named field background pictures.

The train-test-split() method is used to split our data into train and test sets. First, we need to divide our data into features (X) and labels (y). The data frame gets divided into X-train, X-test, y-train and y-test. X-train and y-train sets are used for training and fitting the model. The X-test and y-test sets are used for testing the model if it's predicting the right outputs/labels. We can explicitly test the size of the train and test sets. It is suggested to keep our train sets larger than the test sets.

Chapter 5

Evaluation Matrix

To evaluate the performance of algorithms for Human vs AI classification problem, various evaluation metrics have been used. In this subsection, we review the most widely used metrics for the Human vs AI text detection problem. We plot the matrix as Truth vs Prediction where the significance of labels is as follows

- True Positive (TP): When the predicted disease is correct, and the AI system identifies the disease accurately.
- True Negative (TN): When the predicted disease is not correct, and the AI system correctly identifies the absence of disease.
- False Negative (FN): When the predicted disease is not correct, and the AI system fails to identify the disease.
- False Positive (FP): When the predicted disease is not correct, and the AI system falsely identifies the presence of disease.

Note: the cases follow (Prediction - Truth) where 0 signifies Human and 1 signifies AI respectively.

By formulating this as a classification problem, we can define the following metrics

1. Accuracy = (True Negatives + True Positives) / (True Negatives + False Positives + True Positives + False Negatives)
2. Precision = True Positives / (True Positives + False Positives)
3. Recall = True Positives / (True Positives + False Negatives)
4. F-1 Score = (2 * Precision * Recall) / (Precision + Recall)

These metrics are commonly used in the machine learning community and enable us to evaluate the performance of a classifier from different perspectives. Specifically, accuracy measures the similarity between predicted Human and AI text. Precision measures the fraction of all detected AI text that is annotated as AI text, addressing the important problem of identifying which text is written by AI. However, because datasets are often skewed, high precision can be easily achieved by making fewer positive predictions. Thus, recall is used to measure the sensitivity or the fraction of annotated articles that are predicted correctly. F1 is used to combine precision and recall, which can provide an overall prediction performance for detection.

Note that for Precision, Recall, F1, and Accuracy, the higher the value, the better the performance.

Also to measure how close the predicted value of the classifiers will be corresponding to the actual value we use the Log Loss metric. It is a probabilistic value, and the higher the log loss value means that there is a large difference between the actual and predicted values.

$$LogLoss = \frac{-1}{N}\sum_{i=1}^{N}\sum_{j=1}^{M} x_{ij} * log(p_{ij})$$

Where

N – number of samples

M – number of attributes

Xij – indicates whether sample i belongs to class j or not.

Pij – indicates the probability of sample i belonging to class j.

Correlation Matrix A correlation matrix is a table that shows the correlation coefficients between variables. It is a statistical tool that measures the strength and direction of relationships between two or more variables. Each cell in the matrix displays the correlation between two variables, and the diagonal entries are always 1, as each variable perfectly correlates with itself. The correlation matrix is used to summarize data, identify patterns, and make decisions based on the data. It is often used in conjunction with other types of statistical analysis, such as regression techniques like simple linear regression, multiple linear regression, and lasso regression models.

The correlation matrix can be used to analyze the relationships between different variables and identify patterns in the data. It is a powerful tool for summarizing large datasets and visualizing the relationships between variables. The matrix can be created in Excel or other statistical software, and the presentation of the matrix can be customized to show the whole matrix or just the non-redundant bits.

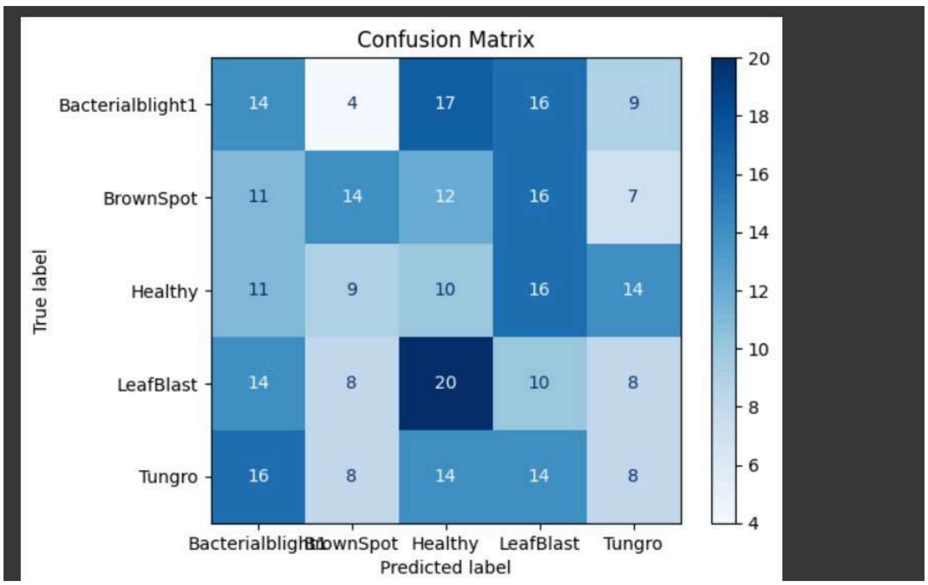
In conclusion, the correlation matrix is a useful tool for analyzing the relationships between variables and identifying patterns in the data.

Chapter 6

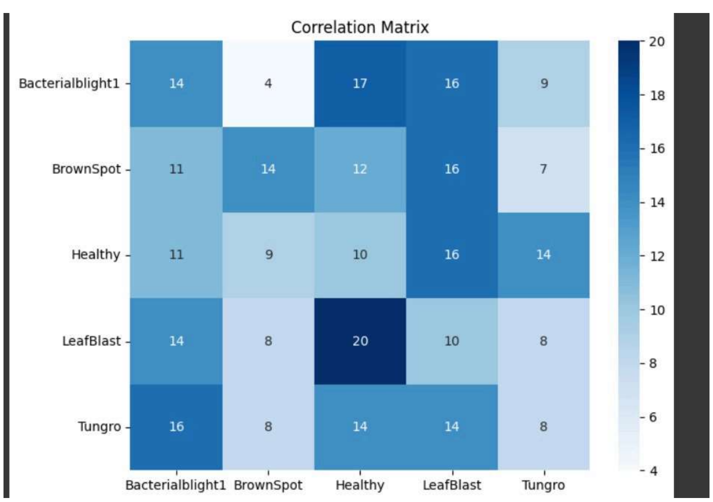
Result and Analysis

Before changing the HyperParameters

Confusion Matrix of MobileNet V2



Correlation Matrix of MobileNet V2



Classification Report of MobileNet V2

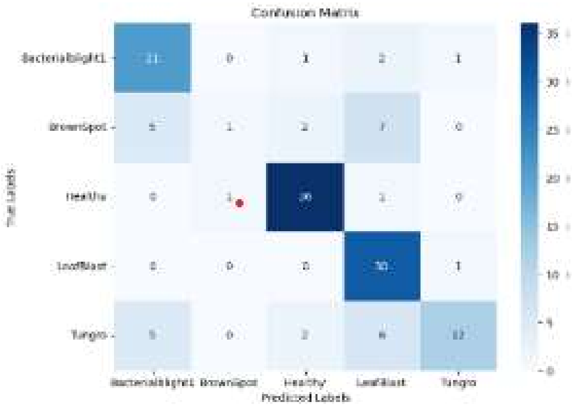
Classification Report:

	precision	recall	f1-score	support
Bacterialblight1	0.21	0.23	0.22	60
BrownSpot	0.33	0.23	0.27	60
Healthy	0.14	0.17	0.15	60
LeafBlast	0.14	0.17	0.15	60
Tungro	0.17	0.13	0.15	60
accuracy			0.19	300
macro avg	0.20	0.19	0.19	300
weighted avg	0.20	0.19	0.19	300

MobileNet V2 Model Accuracy :

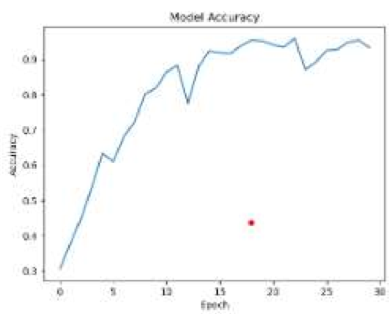
```
50/50 [==============================] - 112s 2s/step - loss: 0.1128 - accur
Epoch 16/30
50/50 [==============================] - 102s 2s/step - loss: 0.1024 - accuracy: 0.9725 - val_loss: 1
Epoch 17/30
50/50 [==============================] - 111s 2s/step - loss: 0.0935 - accuracy: 0.9718 - val_loss: 1
Epoch 18/30
50/50 [==============================] - 112s 2s/step - loss: 0.0774 - accuracy: 0.9787 - val_loss: 1
Epoch 19/30
50/50 [==============================] - 103s 2s/step - loss: 0.0831 - accuracy: 0.9775 - val_loss: 1
Epoch 20/30
50/50 [==============================] - 102s 2s/step - loss: 0.0867 - accuracy: 0.9731 - val_loss: 1
Epoch 21/30
50/50 [==============================] - 114s 2s/step - loss: 0.0688 - accuracy: 0.9800 - val_loss: 1
Epoch 22/30
50/50 [==============================] - 114s 2s/step - loss: 0.0618 - accuracy: 0.9819 - val_loss: 1
Epoch 23/30
50/50 [==============================] - 114s 2s/step - loss: 0.0422 - accuracy: 0.9925 - val_loss: 1
Epoch 24/30
50/50 [==============================] - 112s 2s/step - loss: 0.0405 - accuracy: 0.9919 - val_loss: 1
Epoch 25/30
50/50 [==============================] - 112s 2s/step - loss: 0.0457 - accuracy: 0.9862 - val_loss: 1
Epoch 26/30
50/50 [==============================] - 113s 2s/step - loss: 0.0608 - accuracy: 0.9837 - val_loss: 1
Epoch 27/30
50/50 [==============================] - 101s 2s/step - loss: 0.0567 - accuracy: 0.9825 - val_loss: 1
Epoch 28/30
50/50 [==============================] - 113s 2s/step - loss: 0.0412 - accuracy: 0.9906 - val_loss: 1
Epoch 29/30
50/50 [==============================] - 113s 2s/step - loss: 0.0435 - accuracy: 0.9862 - val_loss: 1
Epoch 30/30
50/50 [==============================] - 101s 2s/step - loss: 0.0358 - accuracy: 0.9906 - val_loss: 1
10/10 [==============================] - 68s 7s/step - loss: 0.3939 - accuracy: 0.9100
Test Accuracy: 0.9100000262260437
```

Confusion Matrix of Efficient Net B0

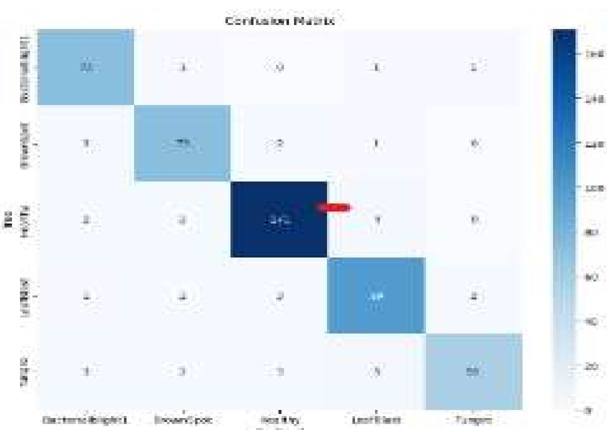


Classification Report of Efficient Net B0

```
80/80 - 130s - loss: 0.1705 - accuracy: 0.9597 - 130s/epoch - 2s/step
Epoch 24/30
80/80 - 130s - loss: 0.4133 - accuracy: 0.8704 - 130s/epoch - 2s/step
Epoch 25/30
80/80 - 131s - loss: 0.3740 - accuracy: 0.8925 - 131s/epoch - 2s/step
Epoch 26/30
80/80 - 131s - loss: 0.2726 - accuracy: 0.9253 - 131s/epoch - 2s/step
Epoch 27/30
80/80 - 135s - loss: 0.2406 - accuracy: 0.9281 - 135s/epoch - 2s/step
Epoch 28/30
80/80 - 131s - loss: 0.1843 - accuracy: 0.9478 - 131s/epoch - 2s/step
Epoch 29/30
80/80 - 131s - loss: 0.1829 - accuracy: 0.9542 - 131s/epoch - 2s/step
Epoch 30/30
80/80 - 136s - loss: 0.2330 - accuracy: 0.9328 - 136s/epoch - 2s/step


5/5 - 2s - loss: 1.2429 - accuracy: 0.7463 - 2s/epoch - 485ms/st
Test Accuracy: 74.63%
5/5 [==============================] - 2s 248ms/step
```



Confusion Matrix of Inception V3



Classification Report Of Inception V3

Classification Report:

	precision	recall	f1-score	support
Bacterialblight1	0.89	0.96	0.92	76
BrownSpot	0.91	0.92	0.92	79
Healthy	0.96	0.96	0.96	179
LeafBlast	0.90	0.93	0.91	107
Tungro	0.95	0.82	0.88	71
accuracy			0.93	512
macro avg	0.92	0.92	0.92	512
weighted avg	0.93	0.93	0.93	512

Classification Report Of SVM model with ORB features

Test Accuracy: 0.6766666666666666

Classification Report (Test Set):

	precision	recall	f1-score	support
1	0.88	1.00	0.94	60
2	0.96	0.38	0.55	60
3	0.43	0.93	0.59	60
4	0.72	0.57	0.64	60
5	0.94	0.50	0.65	60
accuracy			0.68	300
macro avg	0.79	0.68	0.67	300
weighted avg	0.79	0.68	0.67	300

After Changing the Parameters

Classification Report of Efficient Net B0

```
Training with optimizer=adam, learning_rate=0.001, batch_size=32, epochs=100, dropout_rate=0.3
Accuracy: 0.9965665340423584
Training with optimizer=adam, learning_rate=0.001, batch_size=32, epochs=100, dropout_rate=0.5
Accuracy: 0.984549343585968
Training with optimizer=adam, learning_rate=0.01, batch_size=8, epochs=100, dropout_rate=0.3
Accuracy: 0.3390558063983917
Training with optimizer=adam, learning_rate=0.01, batch_size=8, epochs=100, dropout_rate=0.5
Accuracy: 0.3390558063983917
Training with optimizer=adam, learning_rate=0.01, batch_size=16, epochs=100, dropout_rate=0.3
Accuracy: 0.9231759905815125
Training with optimizer=adam, learning_rate=0.01, batch_size=16, epochs=100, dropout_rate=0.5
Accuracy: 0.7248926758766174
Training with optimizer=adam, learning_rate=0.01, batch_size=32, epochs=100, dropout_rate=0.3
Accuracy: 0.9866952896118164
Training with optimizer=adam, learning_rate=0.01, batch_size=32, epochs=100, dropout_rate=0.5
Accuracy: 0.9008583426475525
Best Hyperparameters:
{'optimizer': 'adam', 'learning_rate': 0.0001, 'batch_size': 8, 'epochs': 100, 'dropout_rate': 0.5, 'units_fc': 256}
Best Accuracy: 1.0
```

Accuracy increase from 74.63% to 99.82%

Classification Report Of Inception V3

```
ombination: LR=0.1, Epochs=100, Optimizer=adam, Reg=12, Accuracy: 0.8897058963775635
ombination: LR=0.1, Epochs=100, Optimizer=sgd, Reg=12, Accuracy: 0.8602941036224365
ombination: LR=0.1, Epochs=100, Optimizer=adagrad, Reg=12, Accuracy: 0.7683823704719543

est Hyperparameters:
earning Rate: 0.01
pochs: 100
ptimizer: adam
egularizer: 12
est Test Accuracy: 0.9136029481887817
mohit_venv) mohit@Basant:~/lakshay20dcs015$
```

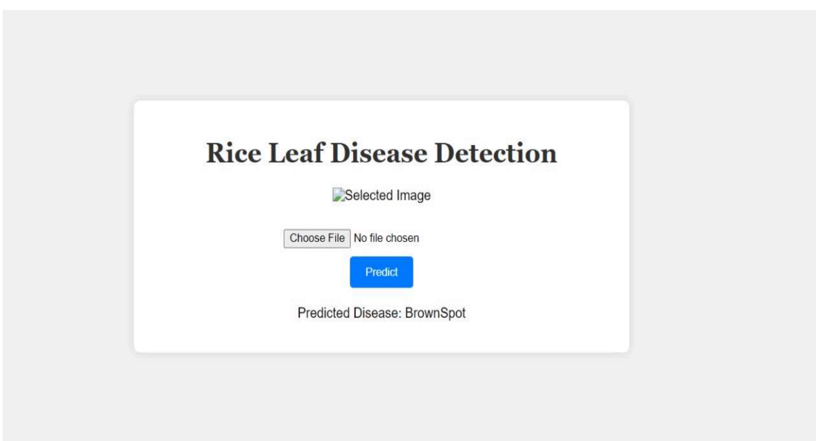
Accuracy increase from 89% to 91.36%

We change the hyperparameters only on 2 models and after changing the hyperparameters on model (EfficientNet B0, InceptionNet V3) accuracy increase form

EfficientNet B0 :- 74.63% to 99.82%

Inception V3 :-   89% to 91.36%

INTERFACE OVERVIEW OF OUR WORK



Chapter 7

CONCLUSION AND FUTURE SCOPE

Conclusion

In conclusion, this project focused on addressing the critical issue of rice plant diseases, which significantly impacts global food security due to its status as a staple food, especially in Asian countries. Leveraging deep learning techniques, particularly Convolutional Neural Networks (CNNs), we explored the performance of four different models for image classification tasks: MobileNet V2, EfficientNet B0, Inception V3, and SVM with ORB features. Each model offered unique strengths and contributed to our understanding of the capabilities of modern machine learning architectures.

The results of the proposed procedure demonstrated a superior performance compared to existing state-of-the-art methods. With an average identification accuracy of 99.67% on a public dataset, the model showcased its effectiveness in precisely identifying various rice plant diseases. Even under complex environmental conditions, the accuracy remained impressively high at 99.82% using the EfficientNet B0 model. These findings underscore the robustness and efficiency of the developed methodology for rice disease identification.

In summary, the key findings of this project are:

- EfficientNet B0 achieved the highest accuracy of 99.82%.
- Inception V3 achieved an accuracy of 91.36%.
- MobileNet V2 achieved an accuracy of 91%.
- SVM with ORB features achieved an accuracy of 67%

Our experiments shed light on the strengths and weaknesses of each model. Moving forward, further optimization and fine-tuning of hyperparameters could potentially enhance the performance of all models. Additionally, exploring ensemble methods that combine the predictions of multiple models could lead to further improvements in accuracy and robustness.

Moreover, considering the specific requirements and constraints of the target application, such as computational resources and deployment environment, will be crucial in selecting the most suitable model for real-world deployment.

Overall, this project serves as a valuable exploration of different neural network architectures and traditional machine learning approaches for image classification tasks, providing insights that can inform future research and practical applications in various domains.

Future Scope:

While the project has achieved remarkable success in the identification of rice plant diseases using MobileNet-V2, there are several avenues for future research and enhancement:

Expansion of Disease Classes:

- Extend the model to identify a broader range of rice plant diseases to enhance its practical utility in diverse agricultural settings.

Real-Time Implementation:

- Explore the feasibility of implementing the model in real-time scenarios, enabling farmers to receive instantaneous feedback on the health of their crops.

Integration of Sensor Data:

- Investigate the integration of additional sensor data, such as environmental conditions and soil health, to enhance the model's predictive capabilities and robustness.

Mobile Application Development:

- Develop a user-friendly mobile application that integrates the trained model, empowering farmers with an accessible tool for on-the-spot disease identification.

Collaboration with Agricultural Experts:

- Collaborate with agricultural experts and stakeholders to gather more diverse and comprehensive datasets, ensuring the model's effectiveness across various regions and conditions.

Fine-Tuning for Local Varieties:

- Fine-tune the model for specific regional or local rice varieties to enhance its applicability in different geographic locations.

Scaling to Other Crops:

- Extend the developed methodology to identify diseases in other crops, contributing to a holistic approach to agricultural disease management.

In pursuing these future directions, the project can contribute further to the advancement of precision agriculture and sustainable farming practices, ultimately benefiting global food production and security.

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