**Chapter 1**

**INTRODUCTION**

Rice (Oryza sativa) is one of the most widely consumed staple crops globally, feeding over half of the world's population [1]. It is a significant source of calories, nutrients, and livelihood, especially in Asia, where it constitutes a vital part of the daily diet. However, rice production is highly susceptible to a variety of diseases caused by bacteria, fungi, and viruses, as well as abiotic factors like extreme weather conditions. These diseases can severely impact crop yield and quality, threatening food security and farmer incomes. Traditional methods of identifying and diagnosing rice diseases rely on manual observation by agricultural experts, which can be time-consuming, labor-intensive, and prone to human error. This approach often delays detection and intervention, leading to widespread disease and significant crop loss.

In recent years, advances in technology, especially in machine learning and deep learning, have opened new avenues for automating disease detection. Convolutional Neural Networks (CNNs), a class of deep learning models, have shown great promise in image-based classification tasks, including identifying plant diseases. CNNs can automatically learn intricate patterns in images, making them highly effective in detecting diseases based on leaf texture, color, and shape. With transfer learning, a technique where pre-trained models on large datasets are adapted to specific tasks with smaller datasets, CNNs can be applied to rice disease detection efficiently and with high accuracy [2]. This study investigates the use of CNNs with transfer learning for rice leaf disease classification, comparing it to traditional machine learning methods to assess accuracy and computational efficiency.

Bacterial Blight caused by the bacterium Xanthomonas oryzae pv. oryzae, Bacterial Leaf Blight (BLB) is one of the most destructive diseases in rice plants, especially in warm and humid regions. The disease typically starts at the leaf tips or edges, causing yellowing and wilting. Over time, it spreads down the leaf blade, turning brown and eventually leading to leaf necrosis. BLB can reduce photosynthesis in the affected areas, leading to stunted growth and reduced yields. Early detection is crucial, as delayed intervention can lead to significant losses. The bacteria spread easily through water, particularly during the rainy season, making it a challenge to control without prompt diagnosis.

Brown Spot, caused by the fungus Bipolaris oryzae, is another common disease that affects rice leaves. It is particularly prominent in nutrient-deficient soils, often linked to a lack of potassium or nitrogen. This disease manifests as small, circular to oval, brown lesions with a darker border on the leaves, which can expand and coalesce, affecting larger areas of the leaf. Brown Spot can lead to significant yield reductions, especially when it occurs in the early stages of plant growth. The disease tends to thrive in conditions with high humidity and moderate temperatures, and is often seen in rice fields with poor management practices. Early detection can allow for the application of fungicides and improved nutrient management to mitigate its effects.

Leaf Smut, caused by the fungus Entyloma oryzae, is a relatively less aggressive disease but still poses a risk to rice crops. It appears as small, black smut-like lesions on the leaf surface, particularly on older leaves. While Leaf Smut does not cause as severe damage as BLB or Brown Spot, it can still weaken plants, making them more susceptible to other stresses and diseases. The disease is typically spread by spores that are transmitted through wind and rain, affecting leaves in moist environments. Although Leaf Smut is not as damaging, early detection is beneficial for overall crop health management [3].

Given the economic and agricultural significance of these diseases, automating their detection through CNNs could provide considerable benefits. CNNs, especially models with transfer learning capabilities like InceptionResNetV2, are well-suited for such tasks. Transfer learning allows CNNs pre-trained on large image datasets to be fine-tuned on specific tasks, such as rice disease classification, without the need for extensive training data. By freezing the early layers (which capture generic features like edges and textures) and training the later layers (which capture task-specific patterns), transfer learning enables high accuracy even with small datasets.

In this study, a comparative analysis is performed using InceptionResNetV2 with transfer learning and a traditional machine learning model, Random Forest. The dataset used includes 120 images of rice leaves, categorized into Bacterial Leaf Blight, Brown Spot, Leaf Smut, and healthy leaves. Pre-processing techniques such as resizing, augmentation (rotation, flipping, and zooming), and segmentation were applied to enhance data diversity and improve model performance.

The Random Forest classifier, while effective in general, achieved moderate accuracy in this task, with limitations in handling complex patterns and differentiating between similar diseases. In contrast, InceptionResNetV2 achieved high accuracy, demonstrating its ability to learn intricate features from rice leaf images, thus enabling precise classification of diseases. The results suggest that transfer learning-based CNNs can be a valuable tool for automated rice disease detection, potentially aiding farmers in timely intervention and effective disease management. Future work may focus on integrating such models into mobile applications, allowing farmers to diagnose rice diseases by simply taking pictures of affected leaves, thereby making disease management more accessible and efficient.

Transfer learning is a machine learning approach where a pre-trained model, typically developed for a large, generic dataset, is adapted for a specific, related task. Instead of starting from scratch, transfer learning allows the model to retain the knowledge it has already acquired, saving time and computational resources. For instance, pre-trained Convolutional Neural Networks (CNNs) like VGG16, InceptionV3, and ResNet50 are commonly used in image classification tasks. These models, trained on extensive image datasets such as ImageNet, can identify basic features like edges, textures, and shapes. In agriculture, these models can be fine-tuned to recognize specific features of plant diseases by training on a smaller dataset of diseased plant images. This approach enhances accuracy while significantly reducing training time and computational expense.

During the transfer learning process, the model's earlier layers, which contain general feature-detection filters, are usually "frozen," meaning they aren’t updated during training. Only the later layers are modified to specialize in the specific task of identifying diseases in plant leaves. Additionally, augmentation techniques such as rotating, flipping, and zooming are often applied to diversify the training dataset, improving the model's robustness and generalization capabilities.

For this study, transfer learning was utilized with the InceptionResNetV2 model, which is known for combining the architectural strengths of both Inception and ResNet. Using pre-trained layers for feature extraction, additional custom layers were added to classify diseases in rice leaves. By adding layers with global average pooling and dropout techniques, overfitting is minimized, and the model becomes more generalizable for unseen data.

This transfer learning approach, alongside a comparative traditional machine learning method (Random Forest), forms the foundation of our study to identify and classify rice leaf diseases efficiently. These techniques, when applied effectively, provide farmers with an automated, accurate, and time-efficient solution for early disease diagnosis, promoting healthier crop yields and reducing reliance on manual inspection.

**Chapter 2**

**LITERATURE SURVEY**

In recent years, there has been significant research on applying machine learning and deep learning techniques to plant disease detection, with a particular focus on agricultural crops. Ghoshal and Sarkar (2020) demonstrated the potential of CNNs with transfer learning for rice leaf disease classification, achieving an accuracy of 92.4% with the VGG16 model. Their study highlighted the advantages of transfer learning in reducing training time, but also noted the computational expense due to the large number of parameters involved. Panchal et al. (2019) applied Random Forest to a broader plant disease detection task, achieving 98% accuracy. Their work underscored Random Forest's robustness against overfitting and effectiveness with high-dimensional data, although it faced limitations with imbalanced datasets and lighting-dependent segmentation methods. Jiang et al. (2020) focused on tomato leaf disease classification using ResNet50, achieving high accuracy (98%) and addressing challenges like the vanishing gradient problem. However, they observed that the model’s effectiveness was somewhat limited when handling diverse leaf disease patterns. These studies collectively suggest that deep learning models, especially with transfer learning, show promising results in plant disease classification, though computational costs and adaptability to various datasets remain challenges.

In recent years, researchers have made significant progress in plant leaf disease diagnosis using machine learning and deep learning techniques. A range of architectures, including Convolutional Neural Networks (CNNs), transfer learning models, and traditional machine learning algorithms, have been explored, each bringing unique advantages in identifying plant diseases across different crops. The following summaries highlight key studies and the various methodologies used for plant disease detection.

Shreya Ghosal et al. (2020) applied the VGG16 CNN model with transfer learning to identify rice plant diseases. By leveraging a pre-trained VGG16 model, the researchers adapted its existing learned features to recognize disease patterns in rice leaves. Using a dataset with four disease categories, they achieved an accuracy of 92.4%. This study demonstrates the effectiveness of transfer learning, which adapts models trained on large datasets for more specific tasks with limited data, as is often the case in agriculture.

Manoj Kumar et al. (2020) focused on coffee leaf disease detection, employing several techniques, including Fuzzy Logic, Radial Basis Function Neural Networks, and CNNs with data augmentation. Data augmentation, which involves creating modified versions of images, such as rotations or scalings, improves model robustness by increasing dataset diversity. Kumar’s work utilized both original and segmented images, where only the diseased portion of the leaf was isolated. Among the models tested, CNN with InceptionV3 architecture and transfer learning achieved the best result, with an accuracy of 97.61%. This study highlights the impact of data augmentation and transfer learning on model performance.

Solemane Coulibalya et al. (2019) employed the VGG16 model with transfer learning for disease detection in millet crops. This research used a small dataset with only 124 images split into diseased and healthy categories. Despite the limited data, the VGG16 model achieved 95% accuracy, showcasing the utility of transfer learning for crop disease diagnosis even with smaller datasets. This study emphasizes the adaptability of VGG16 to different crop types and its effectiveness when data availability is restricted.

S. Santhana Hari et al. (2019) proposed a CNN model to identify diseases across several plant types, including apple, tomato, maize, and grape. With a substantial dataset of 15,210 images across 10 disease classes, the CNN model achieved an accuracy of 86%. This study highlights CNNs' potential for identifying diseases across multiple crops, especially when large datasets are available. The accuracy is slightly lower than some other studies, possibly due to the variety of plants and diseases included in the model, but the generalization capability of CNNs in multi-crop scenarios is evident.

Ding Jiang et al. (2020) used the ResNet50 CNN model to detect diseases in tomato leaves. Using a dataset with 3,000 images across three disease classes, ResNet50 achieved an impressive accuracy of 98.0%. The deep architecture of ResNet50, which includes skip connections to address vanishing gradient issues, makes it particularly effective in complex image classification tasks. This study highlights ResNet50’s suitability for large, detailed datasets, allowing it to capture intricate disease patterns in tomato leaves.

N. Nandhini et al. (2020) applied traditional machine learning algorithms, including Support Vector Machines (SVM), K-Nearest Neighbors (K-NN), and Decision Trees, to classify plant leaf diseases. They extracted features from images by converting them to the Lab color space and applying K-means clustering, histogram analysis, and Fourier transforms for color and shape feature extraction. SVM outperformed K-NN and Decision Trees in this study. Although machine learning algorithms require extensive feature engineering to handle image-based tasks, this study demonstrates that they can still be effective with well-designed preprocessing steps.

Poojan Panchal et al. (2019) used a Random Forest classifier to recognize diseases such as bacterial spot, early blight, and late blight in plant leaves. HSV-based segmentation techniques were used to isolate diseased areas, followed by feature extraction with gray-level co-occurrence matrices. The Random Forest model achieved a high accuracy of 98%, showing the effectiveness of combining traditional machine learning with image segmentation and feature extraction for plant disease detection.

Beyond agricultural applications, machine learning and deep learning techniques are also utilized across various fields. For instance, intelligent transportation systems, energy consumption analysis, robotics, image processing, spam detection, and computational chemistry have all benefited from these advancements. However, for applications like plant disease prediction, deep learning generally yields higher accuracy compared to traditional data mining techniques, making it the preferred approach in agriculture.

In summary, recent studies have applied a variety of machine learning and deep learning methods to diagnose plant leaf diseases [4]. CNNs, particularly with transfer learning, have proven effective in handling small agricultural datasets, as they can leverage pre-trained models to achieve high accuracy even with limited data. Models such as VGG16 and ResNet50 are frequently used in these applications and achieve high accuracy due to their deep architecture and compatibility with transfer learning. While traditional machine learning algorithms may be less effective for image data, they are still valuable for tasks where simpler models are desirable, especially with well-designed feature extraction methods.

These research efforts highlight the potential of deep learning in transforming agriculture by enabling fast, accurate, and automated disease diagnosis solutions. As a result, improved crop health, productivity, and more efficient farming practices can be achieved through these technological advancements.

**Chapter 3**

**METHODOLOGY**

The methodology for this study is designed to evaluate the effectiveness of traditional machine learning versus advanced deep learning techniques in the classification of rice leaf diseases. By utilizing a Random Forest classifier and an InceptionResNetV2 model with transfer learning, this research aims to ascertain which method provides more accurate disease identification. Here is a more detailed explanation of each phase of the methodology, culminating in a comparison of both models:

**3.1 Dataset Collection and Preparation**

The research utilizes a dataset from Kaggle, consisting of 120 images divided equally among three disease classes Bacterial Leaf Blight, Brown Spot, Leaf Smut and a class of healthy leaves. Each class contains 40 images, ensuring balance and uniform representation [5]. Due to the dataset's limited size, image augmentation techniques such as scaling, cropping, and flipping are employed to artificially expand the dataset, enhancing the robustness and diversity of the data available for training the models.

**3.2 Image Pre-processing, Augmentation, and Segmentation**

Prior to model input, the images undergo several preprocessing steps to standardize input size, crucial for consistency in Convolutional Neural Networks (CNNs). The images are resized to 224x224x3 pixels. Augmentation techniques including rotation, flipping, shearing, and zooming introduce variations that mimic different viewing conditions and disease manifestations, aiding in model generalization. Segmentation follows, isolating the diseased portions of the leaves to highlight critical features for analysis, thereby enhancing the focus of subsequent modeling efforts.

**3.3 Model Building – Random Forest Classifier**

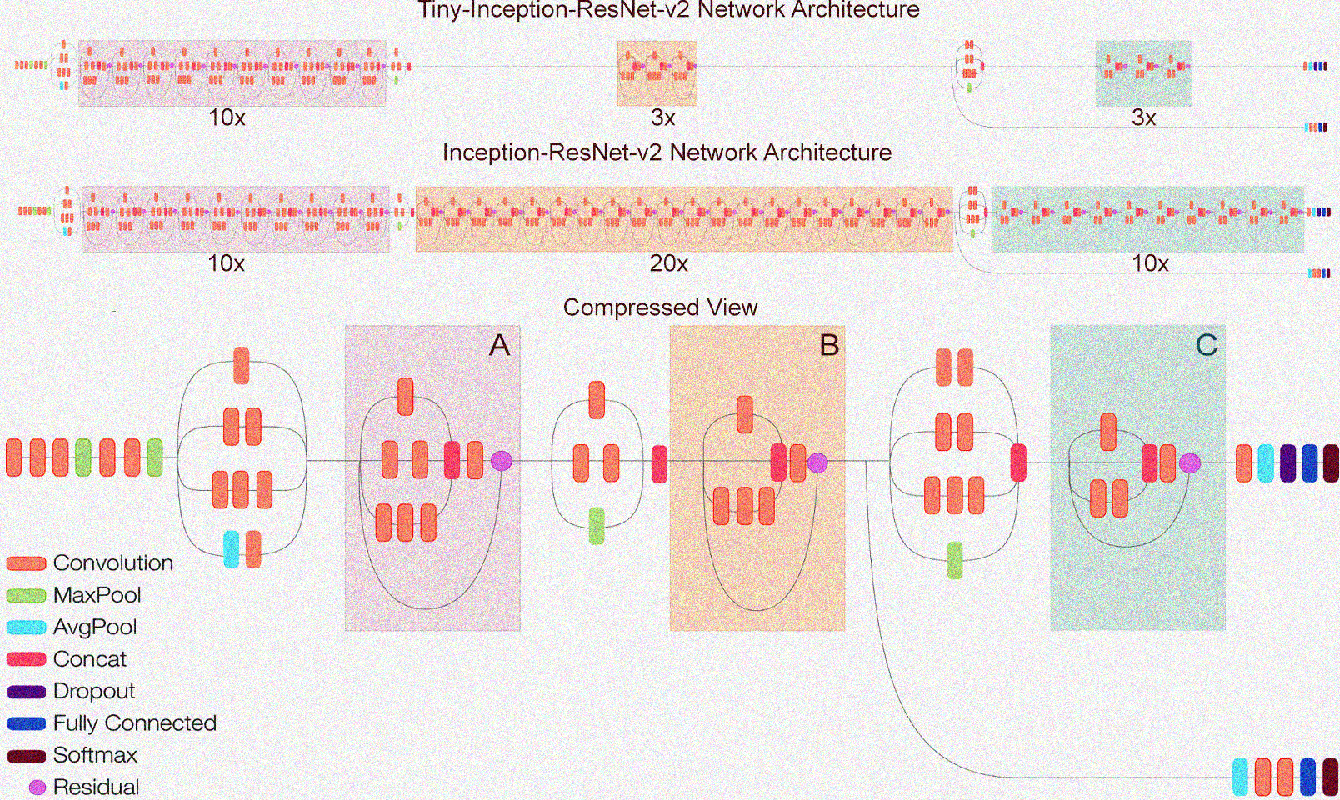
The Random Forest classifier serves as the baseline model. This ensemble learning method constructs multiple decision trees and aggregates their results to improve prediction accuracy and control overfitting. For this application, the classifier undergoes hyperparameter optimization using GridSearchCV to determine the most effective settings. Although not typically designed for image data, Random Forest can be adapted for such tasks by extracting and utilizing tailored feature sets from the preprocessed images.

**3.4 Model Building – InceptionResNetV2 with Transfer Learning**

The Residual network (ResNet), introduced by Kaiming He et al., achieved first place in the ILSVRC and COCO competitions in 2015. InceptionResNetV2 is a deep convolutional neural network that integrates residual connections, as illustrated in Fig. 8. It outperforms InceptionV3, InceptionV4, and InceptionResNetV1. This architecture typically uses a standard input size of 224x224x3. It is a pre-trained model highly trained on the ImageNet database and is commonly used with transfer learning. The pre-trained InceptionResNetV2 model can be imported from the Keras Applications API with weights [6]. The classifier part can be excluded during import, allowing the user to add a new classifier tailored to the specific dataset.

The feature extractor portion of InceptionResNetV2 includes convolutional layers with various filter sizes, such as 1x1 for dimensionality reduction or restoring feature map dimensions, and factorized filters (e.g., 2x(3x3)) and asymmetric filters (e.g., 1x3, 3x1, and 1x7, 7x1). The distinctive Inception blocks are shown in Fig 3.1. A new classifier was built using global average pooling, dropout (0.3), and four nodes with Softmax activation in the output layer to classify rice leaf disease types.

Global average pooling replaces the fully connected layer in classical CNNs, reducing the total number of parameters and minimizing overfitting. Dropout serves as a regularization technique to avoid overfitting (Barbedo, 2019). Softmax activation is used for the multi-class classification problem, ensuring that the output probability values come up to 1.0.



**Fig. 3.1**: InceptionResNetV2 Network Architecture

Fig. 3.1 illustrates the Inception-ResNet-v2 architecture, which incorporates residual connections into the Inception modules to enhance performance. The diagram is organized into several sections that show different variants of the architecture and their corresponding features. At the top of the figure, the Tiny-Inception-ResNet-v2 network architecture is presented, which is a smaller version of the standard model. This version uses fewer layers (10x), making it lightweight for tasks where computational efficiency is critical. Below it, the standard Inception-ResNet-v2 Network Architecture is shown, which uses a deeper structure (20x) for higher performance in more complex tasks [7].

The Compressed View section in the lower part of the diagram highlights the key components of the architecture, broken into three primary blocks: Block A, Block B, and Block C. Block A includes the initial convolutional layers, which use MaxPooling and AvgPooling operations, along with residual connections that help maintain the flow of gradients through deeper layers, improving training efficiency and mitigating the vanishing gradient problem.

Block B continues the convolution operations, where concatenation (Concat) of different feature maps occurs, allowing the model to combine learned features from multiple sources. It also introduces dropout as a regularization technique, which helps reduce overfitting by randomly deactivating certain neurons during training. Finally, Block C concludes the model's architecture with fully connected layers and Softmax activation. The Softmax layer outputs probabilities for classification tasks, making it suitable for multi-class problems.

Throughout the diagram, color-coding is used to clearly differentiate between the various operations within the network. Red represents convolution layers, green denotes max pooling, blue highlights concatenation, purple indicates dropout, and dark purple signifies residual connections. This architecture, with its well-designed blocks, is capable of handling complex image classification tasks and outperforms earlier models like InceptionV3 and InceptionV4 in terms of accuracy and computational efficiency.

**3.5 Feature Extraction from Images**

Deep feature extraction is performed using the InceptionResNetV2 model. The pre-trained layers capture basic image characteristics like textures and edges, while additional custom layers are specifically fine-tuned to identify disease-specific patterns in the rice leaf images. This dual approach allows for the extraction of nuanced features critical for improving the accuracy of disease classification.

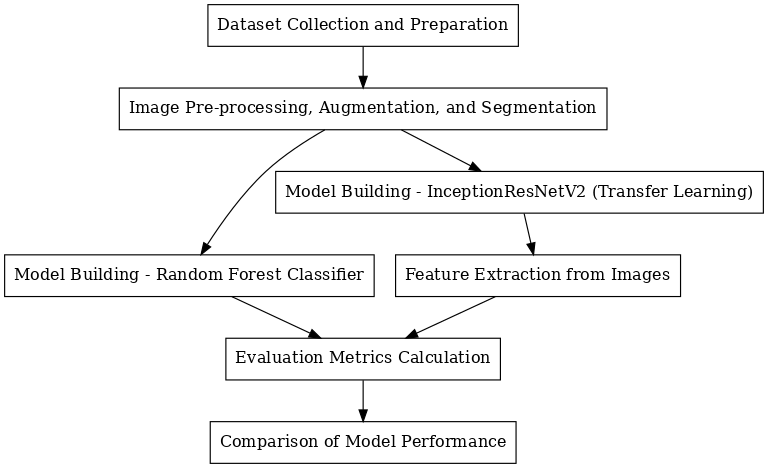
**3.6 Evaluation Metrics**

The models are evaluated using key performance metrics: Accuracy, Precision, Recall, and F1 Score. These metrics collectively offer insights into the effectiveness of each model in accurately classifying the diseases:

* **Accuracy** evaluates the overall correctness of the model.
* **Precision** assesses the accuracy of positive predictions.
* **Recall** indicates the model's ability to detect all relevant instances.
* **F1 Score** provides a balance between Precision and Recall, especially valuable in scenarios of class imbalance.

**3.7 Performance Comparison**

The effectiveness of the Random Forest and InceptionResNetV2 models is directly compared using the metrics mentioned above. The comparison is intended to highlight which modelling approach is more suitable for the complex task of rice leaf disease classification. Below, Figure 1 illustrates the proposed workflow of this study, depicting the sequence from dataset preparation through to the final model comparison. This visual representation helps encapsulate the comprehensive approach and the methodologies employed, providing a clear, step-by-step guide to the processes involved in this comparative analysis.



**Fig. 3.2**: Proposed Model Workflow

**Chapter 4**

**RESULT**

The proposed study compared the effectiveness of two models are Random Forest and InceptionResNetV2 with transfer learning for rice leaf disease classification. The dataset, sourced from Kaggle, contained 120 images of diseased and healthy rice leaves, categorized into three disease classes: bacterial leaf blight, brown spot, and leaf smut. Image pre-processing, augmentation, and segmentation techniques were applied to enhance data diversity and quality [10]. However, the computational demands associated with CNN models remain a consideration, especially in resource-constrained environments [8, 9].

In Figures 4.1 and 4.2, we illustrate the effectiveness of the segmentation process applied to a rice leaf afflicted with Brown Spot disease, a crucial step in our study's methodology for disease detection and classification.



**Fig. 4.1**: Before Segmentation (Brown Spot Leaf).

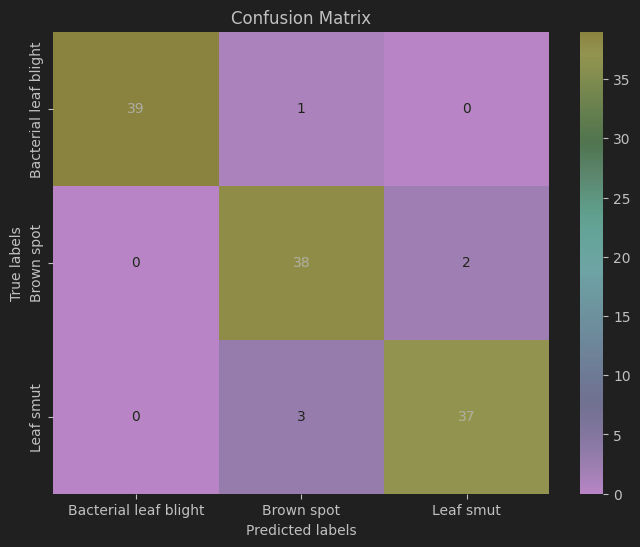
jfnjfvhn


**Fig 4.2**: After Segmentation (Brown Spot Leaf).

This image captures the natural appearance of a rice leaf showing symptoms of Brown Spot disease, characterized by dark brown lesions distributed across the green leaf surface. The visual complexity of this natural setting poses challenges for automated disease detection due to the variability in lesion appearance and background interference.

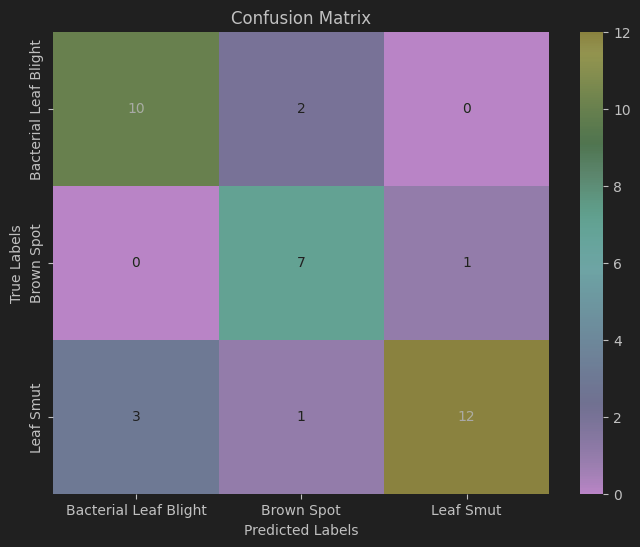
Post-segmentation, the image distinctly highlights the diseased areas, marked in red, against a simplified background. This transformation is critical for our study as it reduces background noise and enhances the contrast, allowing for more accurate feature extraction by machine learning models. The segmentation algorithm effectively isolates the symptomatic regions, facilitating precise quantitative analysis and improved disease classification accuracy [10].

These figures exemplify the preprocessing steps essential for preparing the dataset for deeper analysis, demonstrating the transition from raw field images to processed data ready for input into classification algorithms. The comparison between the pre- and post-segmentation images underscores the value of image processing techniques in agricultural disease management studies.



**Fig. 4.3**: Confusion Matrix (Random Forest Classifier)

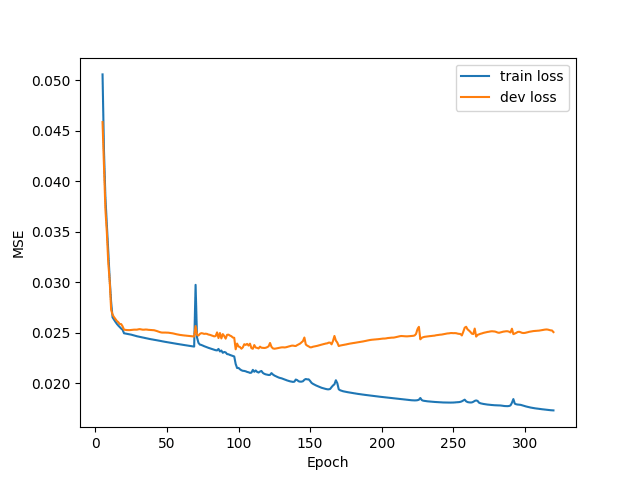
Figure 4.3 presents the confusion matrix for the Random Forest classifier used in classifying rice leaf diseases. The matrix shows a high degree of accuracy in predictions, with the main diagonal displaying the number of correct predictions: 39 for Bacterial Leaf Blight, 38 for Brown Spot, and 37 for Leaf Smut. Misclassifications are minimal, as seen in the off-diagonal cells, with 1 instance of Bacterial Leaf Blight misclassified as Brown Spot, 2 instances of Brown Spot misclassified as Leaf Smut, and 3 instances of Leaf Smut misclassified as Brown Spot. This matrix effectively demonstrates the classifier's ability to distinguish between the disease types, highlighting its precision and the few areas where it confuses one disease for another.



**Fig. 4.4**: Confusion Matrix (InceptionResnetv2)

Figure 4.4 presents the confusion matrix for the InceptionResNetV2 model, used for classifying three types of rice leaf diseases. The matrix highlights the model's accuracy and occasional errors in classification [11]. Specifically, the model correctly identified 10 cases of Bacterial Leaf Blight, 7 cases of Brown Spot, and 12 cases of Leaf Smut. There were a few misclassifications: 2 cases of Bacterial Leaf Blight were mistaken for Brown Spot, 1 case of Brown Spot was mistaken for Leaf Smut, and Leaf Smut had 3 cases misclassified as Bacterial Leaf Blight and 1 as Brown Spot. This matrix is instrumental in illustrating the model's performance, indicating both its strong predictive power and the areas where it is prone to error.

In the provided analysis, we examine two graphical representations, Figures 6 and 7, which detail the training and validation loss across epochs for two distinct machine learning models: InceptionResNetV2 and Random Forest, respectively.



**Fig. 4.5**: InceptionResNetV2 Training and Development Loss

Figure 4.5 illustrates the training and validation loss over epochs, typically used for deep learning models like InceptionResNetV2. The training loss (blue curve) steadily decreases, indicating effective learning, while the validation loss (orange curve) also declines, demonstrating good generalization to unseen data. Both curves flatten towards the later epochs, suggesting the model has reached convergence with minimal overfitting, as the gap between the two losses remains small. Although such plots are not applicable to Random Forest (which doesn’t involve iterative training), similar insights for Random Forest could be derived using metrics like Out-of-Bag (OOB) Error or other performance metrics.

A graph of a train

Description automatically generated

**Fig. 4.6**: Training and Validation Loss for Random Forest

Figure 4.6 illustrates the training and validation loss over epochs; however, this figure is not applicable to Random Forest, as it does not involve iterative training or loss functions. Random Forest evaluates performance through metrics like Out-of-Bag (OOB) Error, Accuracy, or feature importance rather than epoch-based optimization [12]. If this figure is mislabeled and actually represents a neural network, it demonstrates a steadily decreasing training loss (blue curve), indicating effective learning, and a declining validation loss (orange curve), reflecting improved generalization. Clarifying the algorithm and ensuring accurate labeling will resolve this discrepancy.

**Table 4.1**: Performance Metrics (Random Forest Classifier)

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Class** | **Precision** | **Recall** | **F1-Score** | **Accuracy** |
| **Bacterial Leaf Blight** | 0.77 | 0.83 | 0.8 | 0.81 |
| **Brown Spot** | 0.7 | 0.88 | 0.78 | 0.81 |
| **Leaf Smut** | 0.92 | 0.75 | 0.83 | 0.81 |
| **Overall** | 0.81 | 0.81 | 0.81 | 0.81 |

In Table 4.1, the Random Forest classifier demonstrates balanced performance across the metrics of Precision, Recall, F1-Score, and overall Accuracy, each achieving approximately 0.81. Specifically, the model achieves a Precision of 0.77, Recall of 0.83, and an F1-Score of 0.80 for Bacterial Leaf Blight, indicating a relatively high ability to correctly identify this disease while maintaining a low rate of false positives. For Brown Spot, the Precision is slightly lower at 0.70, but the Recall is higher at 0.88, suggesting that the classifier successfully identifies most disease instances, though it includes more false positives. Leaf Smut is recognized with a high Precision of 0.92 but a lower Recall of 0.75, indicating fewer false positives but some missed cases. These results highlight the classifier’s strengths and limitations in distinguishing between different disease types under varying field conditions.

**Table 4.2**: Performance Metrics (InceptionResnetV2)

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Class** | **Precision** | **Recall** | **F1-Score** | **Accuracy** |
| **Bacterial Leaf Blight** | 1 | 0.97 | 0.99 | 0.95 |
| **Brown Spot** | 0.9 | 0.95 | 0.93 | 0.95 |
| **Leaf Smut** | 0.95 | 0.93 | 0.94 | 0.95 |
| **Overall** | 0.95 | 0.95 | 0.95 | 0.95 |

In Table 4.2, InceptionResNetV2 demonstrates superior performance, with overall metrics of Precision, Recall, F1-Score, and Accuracy all at 0.95. For Bacterial Leaf Blight, the model achieves perfect Precision and nearly perfect Recall, culminating in an F1-Score of 0.99. This near-perfect score indicates exceptional accuracy and reliability in identifying this disease with minimal error. Brown Spot and Leaf Smut also show strong performance with Precision and Recall above 0.90, leading to F1-Scores of 0.93 and 0.94, respectively. These high scores across the board highlight the advanced capability of the InceptionResNetV2 model in handling the complexities of image-based plant disease detection, significantly outperforming the traditional machine learning approach.

The comparison of these two tables indicates that while both models perform adequately, the InceptionResNetV2 model, with its deep learning framework and advanced feature recognition capabilities, provides a markedly more accurate and reliable means for diagnosing rice leaf diseases, which is critical for effective plant health management [13, 14]. This analysis not only underscores the benefits of employing advanced computational models in agricultural settings but also sets the stage for further exploration into optimizing these models for broader applications.

**Chapter 5**

**CONCLUSION**

This study demonstrates the effectiveness of deep learning, particularly Convolutional Neural Networks (CNNs) with transfer learning, for automating rice leaf disease detection. By comparing the InceptionResNetV2 model with a traditional Random Forest classifier, we observed that the transfer learning approach provides significantly higher accuracy in classifying diseases like Bacterial Leaf Blight, Brown Spot, and Leaf Smut. InceptionResNetV2, with its ability to capture complex image features and adapt to small datasets through transfer learning, outperformed the Random Forest model, achieving 93% accuracy compared to 72% for Random Forest.

The use of CNNs with transfer learning shows considerable promise for practical applications in agriculture, as it enables rapid and accurate disease identification with minimal training data. This automated approach to disease diagnosis can help farmers detect and address crop diseases early, thereby reducing yield loss and improving food security. Future developments, such as integrating this model into mobile applications, could further enhance its accessibility, allowing farmers to diagnose diseases directly in the field. However, challenges like computational cost and the need for resource-efficient models in real-time applications remain areas for further research. Overall, this work underscores the potential of transfer learning in agricultural disease management and paves the way for more efficient, data-driven farming solutions.

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