Paddy Leaf Diseases Classification Using Transfer Learning Models

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***Abstract* - Rice is a crucial source of sustenance for millions of people, especially in Asia. Paddy leaf diseases significantly threaten rice production, resulting in lower yields, reduced quality, and increased costs. Early detection and treatment are crucial to mitigate these losses, but identifying the diseases accurately can be challenging and time-consuming for farmers. In this research, we introduce a paddy leaf disease detection system based on deep learning. The system is capable of classifying five distinct types of paddy diseases as well as identifying healthy paddy leaves. The classification is achieved through the implementation of ResNet-50, VGG16, and ResNet101v2 models. We trained our models on a publicly available image dataset from public platform Kaggle, and the results indicates that the ResNet-50 model achieved the highest accuracy of 98% on the dataset. The VGG16 model achieved an accuracy of 92%, and the ResNet101v2 model achieved an accuracy of 93%. These models effectively extract complex features from images and improve the accuracy of identifying diseases. By leveraging the power of deep learning, we can help farmers detect and treat paddy diseases more efficiently, ultimately protecting their crops, ensuring food security, and driving economic growth in the agricultural sector.**

Keywords: *deep learning, ResNet50, image processing, Paddy leaf disease*

I. INTRODUCTION

The agricultural sector in India holds great significance in supporting the livelihoods of millions of individuals, where rice farming emerges as a critical pillar of the industry. However, the occurrence of rice plant diseases has become a common cause of farmers' low yields and reduced income. Indeed, rice plant diseases present a significant global challenge to food security, with over 800 million people lacking access to sufficient food due to such issues. Identifying and diagnosing rice leaf diseases has therefore become a significant challenge for the agricultural industry. Traditional methods of detection require a wealth of knowledge and experience, making it a time-consuming and challenging task. Furthermore, the use of chemicals to treat such diseases is not always an appropriate solution, especially with the potential harm they may cause to the environment and human health. Hence, accurate and efficient identification of rice leaf diseases can help in finding an early remedy and prevent significant crop losses. This study presents an innovative methodology for the identification of rice diseases using Convolutional Neural Networks (CNNs). CNN techniques have proven to be highly effective in extracting features and classifying data, making them well-suited for our research. The main aim of our proposed approach is to improve the accuracy of rice disease identification and detection, thereby ensuring the quantity and quality of rice production. Early detection is of utmost importance as it plays a pivotal role in maintaining robust plant growth and optimizing yield, thereby contributing significantly to addressing global food security concerns.

In a previous study [1], the classification of rice leaf diseases was conducted using the Minimum Distance Classifier (MDC) and k-Nearest Neighbour classifier (k-NN). Although these methods displayed promising results, the rapid progress of technology has introduced Convolutional Neural Networks (CNNs) as a highly effective approach for feature extraction and classification. CNNs have demonstrated significant potential in various domains by autonomously learning from past events, making informed decisions, and automatically detecting crucial features without the need for human supervision. Moreover, CNNs require only a limited number of images for training and testing, rendering them a promising tool for accurately identifying rice leaf diseases. After the emergence of Convolutional Neural Networks (CNNs) was changed the performance in domains like image classification, object identification, picture segmentation, etc., are the most common deep learning models used for computer vision issues. Currently, there have been advancements in the automated detection of plant diseases using plant photos. InceptionV3, ResNet50, and VGG-16 are popular choices for training large convolutional neural models on extensive datasets. These models have proven to be highly effective in extracting meaningful features from plant images, enabling accurate and efficient detection of various plant diseases. Transfer learning is a popular deep learning strategy that entails using previously taught models to solve a comparable problem. The primary objective of the study mentioned in [2] is to evaluate the performance of deep convolutional neural networks (CNNs) with transfer learning in identifying various diseases in rice plant leaves. The research aimed to expedite the training process and enhance the effectiveness of the neural network by combining CNNs with transfer learning methods. The research aimed to improve the precision and effectiveness of rice plant disease identification by utilizing pre-trained models and transferring knowledge from related tasks. In recent times, the recognition and categorization of rice leaf diseases have greatly advanced due to the incorporation of Deep Convolutional Neural Networks (DCNN) and transfer learning methods. A reliable approach has emerged, utilizing transfer learning with VGG19 as the base model, enabling accurate identification and categorization of six specific disease categories: Healthy, Narrow Brown Spot, Leaf Scald, Leaf Blast, Brown Spot, and Bacterial Leaf Blight [3]. By leveraging the strengths of transfer learning and the capabilities of the VGG19 model, this technique offers a robust and precise solution for disease identification in rice leaves.

To improve the precision and effectiveness of the identification process, the study introduces a Rectified Linear Unit (ReLU) classifier. The proposed approach synergistically utilizes Convolutional Neural Networks (CNNs) in conjunction with pre-trained models, including ResNet-50, ResNet-101, VGG-16, VGG-19, EfficientNet, Inception-V2, and GoogleNet libraries. In the research paper [4], a method for detecting paddy leaf diseases is introduced, which effectively identifies and diagnoses five distinct types of rice leaf problems. By leveraging this technology, the approach aims to achieve cost-efficiency and maximize rice production, offering advantages over traditional methods. Manual detection of diseases on images is a time-consuming process that relies on expert experience. To overcome this challenge, computerized techniques are employed to enable rapid processing and achieve accurate disease detection results. In these approaches, deep learning models, particularly convolutional neural networks (CNNs), are employed to automatically extract pertinent features from images and subsequently classify them using fully connected networks [5]. By leveraging the power of CNNs, these computerized approaches offer an efficient solution for disease identification, reducing the dependence on manual expertise and streamlining the process.

In the field of Precision Agriculture, high-resolution remote sensing has emerged as a valuable tool. However, traditional classification methods often face challenges when dealing with complex image features. Addressing this concern, a novel CNN-based classification method is introduced in the research paper [6]. The CNN model is trained on a vast dataset of high-resolution satellite images, leading to enhanced crop classification performance. This approach holds significant promise in advancing image analysis techniques within the realm of Precision Agriculture, offering potential improvements in crop monitoring and management.

To achieve rapid classification of paddy leaf diseases, image datasets are employed to distinguish between healthy and diseased rice leaves based on a collection of images. In this study, a classification module is developed utilizing convolutional neural network layers. Additionally, a novel module for image classification using CNN is introduced [7]. By leveraging the power of CNNs, this approach offers a promising solution for efficient and accurate classification of paddy leaf diseases, contributing to improved disease management in rice crops.Rice is a globally significant crop, with its leaves playing a crucial role in the growth and productivity of the plant. In this study [8], the objective was to develop an automated approach using deep learning CNN models for detecting diseases in paddy leaves. The goal was to overcome the limitations of the time-consuming and less accurate traditional manual disease detection process. The paper evaluated four CNN models (VGG-19, Inception-ResNet-V2, ResNet-101, and Xception) and found that the Inception-ResNet-V2 model achieved the highest accuracy of 92.68%. This indicates that the Inception-ResNet-V2 model outperformed the others in accurately identifying and classifying diseases in paddy leaves. The research demonstrates the potential of deep learning techniques to enhance the efficiency and accuracy of disease detection in paddy crops. This [9] presents a novel approach to identify and diagnose paddy leaf diseases using convolutional neural network (CNN) models with various pre-trained libraries such as ResNet-50, ResNet-101, VGG-16, VGG-19, EfficientNet, Inception-V2, and GoogleNet. Leveraging the power of deep learning along with a ReLU classifier, the proposal aims to improve the efficiency of the recognition process. Here the accuracy for all five identifications using the ResNet-50 pre-trained library is reported to be 96.27 percent, with an F1 Score of 98.19 percent. On the other hand, GoogleNet exhibits the lowest classification accuracy of 86 percent. The CNN-based system helps farmers to increasing productivity and enhancing agricultural systems. In [10] approach involves gathering information from various sources on different plant types, which we then accurately label to create a reliable dataset. This dataset encompasses a range of crop diseases, enabling us to achieve high accuracy levels in disease identification. The system provides specific remedies to control each identified disease and achieves an impressive accuracy rate ranging from 94% to 96%. Researchers designed a Convolutional Neural Network (CNN) model for detecting leaf diseases by optimizing network parameters. The model was trained on a dataset containing images representing various types of leaf diseases. The outcomes demonstrated that the proposed model achieved a remarkable training accuracy of 99.78% and a validation accuracy of 97.35% [11]. In the study presented in [12], the authors explore the implementation of deep learning methods to detect diseases and pests in rice plant images. They adopt and fine-tune two state-of-the-art architectures, VGG16 and InceptionV3, achieving promising outcomes with real datasets. Furthermore, to overcome the challenges of deploying large-scale models on mobile devices, they propose a memory-efficient two-stage small CNN architecture. Experimental results reveal that this approach achieves an accuracy of 93.3% while significantly reducing the model size compared to VGG16. In this research [13], a novel method for identifying rice diseases using deep convolutional neural networks (CNNs) is proposed. By training the CNNs on a dataset containing natural images of diseased and healthy rice leaves and stems, the model achieves an accuracy of 95.48% in identifying 10 common rice diseases. The results surpass traditional machine learning approaches, illustrating the effectiveness and feasibility of the proposed method for rice disease identification. The aim of this study [14] is to develop a machine learning-based method that can accurately identify common rice diseases by analyzing clear images of diseased rice leaves.The dataset is pre-processed and trained with various algorithms including KNN, J48, Naive Bayes, and Logistic Regression. The decision tree algorithm achieves a test accuracy of over 97% after 10-fold cross-validation. This approach shows promise for accurately diagnosing rice leaf diseases based on leaf images. Here deep learning approach for image processing and classification tasks, specifically focused on rice disease images. By combining DenseNet and the Inception module, the proposed method achieves remarkable performance surpassing other state-of-the-art techniques. The average predicting accuracy on a public dataset exceeds 94.07%, and when considering multiple diseases, the class prediction accuracy for rice disease images reaches 98.63% [15]. In this research work [16], the authors presented two significant contributions to tackle rice diseases effectively. The study involved curating an infield rice disease image dataset. They utilized various deep learning models, including ResNets and DenseNets, for rice disease classification. The experimental outcomes showed an impressive average accuracy exceeding 95% for their proposed framework. Here the [17] method for detecting and preventing plant leaf diseases in agriculture using image processing and two well-known CNN models, AlexNet and ResNet-50. The technique is applied to datasets of potato and tomato leaves obtained from Kaggle to analyze unhealthy leaf symptoms. By extracting features and performing classification using the CNN models, the proposed approach achieves high accuracies of 97% and 96.1% for ResNet-50, and 96.5% and 95.3% for AlexNet, in classifying healthy-unhealthy leaves and identifying leaf diseases, respectively.

In [18], the authors propose a system utilizing mask R-CNN and Faster R-CNN algorithms for identifying diverse rice plant leaf diseases in the southern region of India to enhance paddy yield. Mask R-CNN demonstrates superior performance with notable detection rates of 96% for Blast, 95% for Brown spot, and 94.5% for Sheath blight. The system's effectiveness in accurately detecting rice blast diseases from real-time leaf images highlights its potential for disease control and improved rice production in various regions. In [19], the authors propose a deep learning method to detect cassava diseases using a dataset of 10,000 labeled images with high-class imbalance and small size. By employing class weights, SMOTE, and focal loss techniques with deep CNNs, they achieve over 93% accuracy, effectively predicting underrepresented classes. This method offers a practical and efficient solution for timely cassava disease detection, aiding food security and famine prevention in Africa. In [20], the authors present an automatic diagnosis method for rice diseases, utilizing an Ensemble Model that integrates three top-performing submodels: ResNeSt-50, SE-ResNet-50, and DenseNet-121. The model achieves an overall accuracy of 91% for diagnosing six types of rice diseases, effectively minimizing confusion among different disease types and reducing misdiagnosis. This approach offers a promising solution for improving crop yield and addressing the negative effects of rice diseases on agriculture. Traditional methods of identifying these diseases through visual inspection are not only time-consuming but also prone to errors. This research paper introduces an innovative solution that utilizes ResNet50, a state-of-the-art deep-learning model, to achieve the precise classification of six distinct types of paddy leaves. The classification encompasses five types of diseased leaves and one category for healthy leaves. By leveraging the capabilities of ResNet50, this cutting-edge solution aims to provide accurate and reliable identification of paddy leaf conditions, enabling efficient disease management in rice crops.

To ensure a coherent structure for our paper, we have outlined the subsequent sections as follows: Section 2 elaborates on our novel methodology, providing an in-depth description of its components and approach, while Section 3 presents the results of our experiments along with a comprehensive analysis and discussion. In Section 4, we wrap up our findings and provide insights into future directions for research. In Section 5, we will provide a concise conclusion summarizing the key takeaways from our study and propose potential avenues for future investigations to enhance and improve our results.

II. METHODS AND MATERIAL

Accurate classification of rice leaf disease plays a crucial role in effective crop health management. In this study, we propose a novel system that utilizes a deep CNN transfer learning-based approach to classify six distinct types of rice leaf disease, namely bacterial leaf blight, brown spot, healthy, leaf scald, leaf blast, and narrow brown spot. The dataset employed for training and evaluation is obtained from the reputable public platform Kaggle [21], ensuring the reliability and diversity of the image samples. By leveraging transfer learning and a comprehensive dataset, our system aims to improve the accuracy and reliability of rice leaf disease classification, contributing to more efficient crop health management. To prevent overfitting and increase the dataset size, the system uses various pre-processing stages such as data augmentation and normalization techniques. For feature extraction, we use the ResNet50 model, which is a pre-trained deep CNN widely used in various computer vision tasks. The proposed system is assessed using several metrics including accuracy, precision, recall, and F1-measure, which indicate that the system outperforms previous studies in the introduction. A visual representation of the system architecture, as shown in Figure 1, illustrates the different stages of pre-processing, feature extraction, classification, and model evaluation, highlighting the efficiency and effectiveness of the proposed approach.

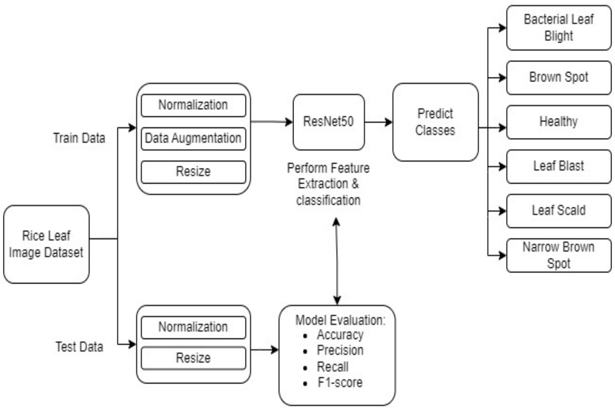
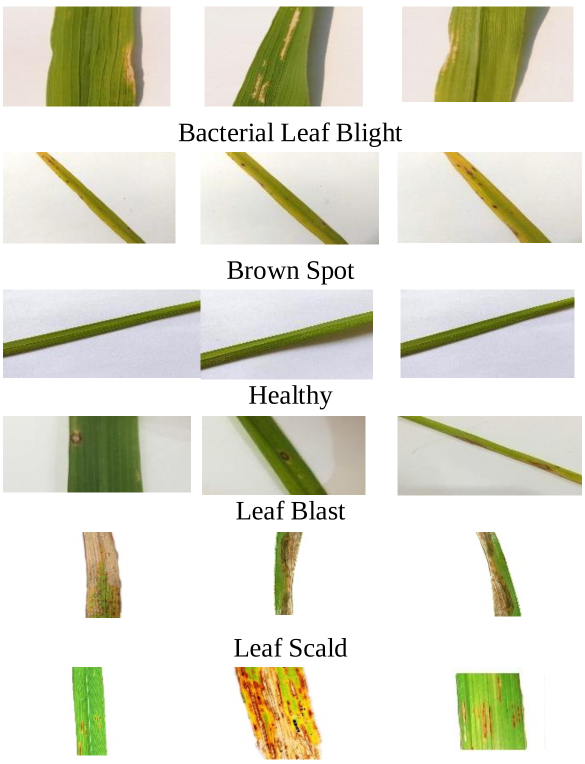


Figure 1. Proposed system architecture

A. *Dataset*

The dataset used in this study, as depicted in Figure 2, was sourced from the public platform Kaggle. It comprised the following quantities of images per category: bacterial_leaf_blight (438 images), brown_spot (466 images), healthy (464 images), leaf_blast (454 images), leaf_scald (448 images), and narrow_brown_spot (440 images).



Narrow Brown Spot
Figure 2. Dataset images

B. *Pre-processing*

Paddy disease classification is a critical task in agricultural research, and accurate diagnosis of these diseases is essential for effective crop management. In this work, we propose a novel pre-processing pipeline that prioritizes normalization, data augmentation, and resizing to improve the performance of paddy disease classification models. Firstly, we apply normalization to the pixel values of the input images to have zero mean and unit variance. Normalization improves the convergence speed of the training process, making the model more stable and robust. This step is crucial for the accurate diagnosis of paddy leaf diseases, as it ensures that the model is trained on consistent and normalized data.

Next, we apply data augmentation techniques to generate additional training data using common techniques such as shear, zoom, horizontal flip, and rotation range. By setting the shear range and zoom range to 0.2, we randomly apply shear and zoom transformations to the input images, which can help the model to better recognize and classify diseased paddy plants that have varying degrees of severity and appearance. The horizontal flip parameter is set to True, which means that we randomly flip the input images horizontally. This can help the model to better recognize diseased paddy plants that have a different orientation or direction of growth. Finally, we set the rotation range to 20, which means that we randomly rotate the input images by a maximum of 20 degrees in either direction. This can help the model to better recognize and classify diseased paddy plants that have different angles or orientations.

Lastly, we resize the input images to a fixed size of 224x224, which is compatible with the chosen classification model, ResNet50. This step enhances the computational efficiency of the model and reduces memory usage, especially when dealing with large-scale datasets. Resizing the images to a consistent size also helps the model generalize better to new and unseen data. By employing a 224x224 resize and utilizing the ResNet50 model, we ensure optimal performance and accuracy in classifying rice leaf diseases.

Our proposed pre-processing pipeline significantly improves the performance of paddy disease classification models by creating more diverse and normalized training data, improving the model's robustness and generalization ability, and reducing computational costs. These improvements result in more accurate and reliable disease diagnosis, which is crucial for sustainable agriculture.

C. *Model building*

Constructing an efficient CNN model from scratch can be difficult, as it requires a significant amount of labeled data and computing resources. Luckily, transfer learning provides a solution to this problem by enabling us to leverage pre-trained weights from a larger dataset to enhance the performance of our model on smaller datasets.Here, we present a CNN model implementation using transfer learning with the ResNet50 architecture for image classification. Our model is trained to classify paddy leaf images into one of six classes, making it a valuable tool for disease detection early. The pre-trained weights on the ImageNet dataset allow us to efficiently leverage the wealth of knowledge learned by the ResNet50 model, while the removal of its fully connected layers allows us to tailor the model to our specific classification task.

To prevent the pre-trained weights from being modified during training, we use a for loop to set all layers in the base model to be non-trainable. To extract features from the output of the base model in our CNN architecture, we employ a GlobalAveragePooling2D() layer. This is followed by a fully connected layer with a ReLU activation function, which helps to introduce non-linearity and capture more intricate patterns in the data. Lastly, we include a fully connected layer with a softmax activation function to transform the output into a probability distribution across the classes.

The CNN model architecture we propose utilizes transfer learning with the ResNet50 architecture, offering a potent solution for image classification tasks, especially with limited datasets. Leveraging pre-trained weights allows our model to enhance its performance on smaller datasets, making it an appealing choice for tasks such as paddy leaf disease detection. In essence, our implementation of the CNN model with transfer learning contributes significantly to the field of computer vision, particularly in the domain of crop disease detection.

D. Model training

This study introduces a novel system for paddy leaf disease detection, employing transfer learning with the ResNet50 architecture in a CNN model. The model is trained on a limited dataset to classify images into six disease classes. During the initial training stage, the model is compiled with an Adam optimizer, employing a learning rate of 0.001 and a categorical cross-entropy loss function. To address the class imbalance, class weights are calculated using the balanced method from the sklearn package. The training process incorporates callbacks such as early stopping, learning rate schedule, and learning rate reduction on plateaus over 30 epochs. In the subsequent training stage, certain layers of the pre-trained model are unfrozen, and the model is recompiled with a lower learning rate of 0.0001. Fine-tuning is performed for an additional 50 epochs, employing the same callbacks and class weights.

Transfer learning and fine-tuning are two techniques used in the training process that greatly improve the performance of the model in paddy leaf disease detection. The pre-trained ResNet50 model has already learned to extract high-level features from the ImageNet dataset, and transfer learning allows us to leverage this knowledge and apply it to our task with a limited dataset. By freezing the layers of the pre-trained model during the first stage of training, the model can learn to extract useful features from the limited dataset. In the second stage of training, unfreezing some of the layers allows the model to fine-tune these features to better fit the task of paddy leaf disease detection. Callbacks, such as early stopping and learning rate reduction on plateaus, are commonly employed during the training process to mitigate overfitting and enhance the model's ability to generalize. Moreover, incorporating class weights during training can help address class imbalance issues and prevent biases towards the dominant class. These techniques are implemented to improve the model's performance, ensure fair representation of all classes, and promote better generalization capabilities. By employing these strategies, the model can achieve better overall accuracy and be more effective in handling diverse and imbalanced datasets. Through transfer learning and fine-tuning, this approach significantly enhances the model's performance in detecting paddy leaf diseases, even with a limited dataset.

III. RESULTS AND DISCUSSION

In this study, we assess the performance of a ResNet50 model specifically developed for the detection of paddy leaf diseases. The model is trained and evaluated on a dataset containing various labels, including bacterial leaf blight, brown spot, healthy leaves, leaf blast, leaf scald, and narrow brown spot. The performance of the model was assessed using a classification report and a confusion matrix, which are commonly utilized for evaluating the effectiveness of classification models. According to the classification report, the model achieved excellent precision, recall, and F1 scores for all classes, indicating its capability to accurately identify various types of paddy leaf diseases with high recall and precision. The F1 score combines precision and recall into a single metric, where a score of 1 signifies perfect precision and recall. The confusion matrix offers a visual representation of the model's predictions versus the actual labels. It aids in assessing the model's ability to correctly classify different types of paddy leaf diseases, with correct predictions shown on the diagonal of the matrix and misclassifications represented by the off-diagonal entries. The confusion matrix provides insights into the model's performance, highlighting its proficiency in accurately classifying most types of paddy leaf diseases while also identifying errors in certain categories.

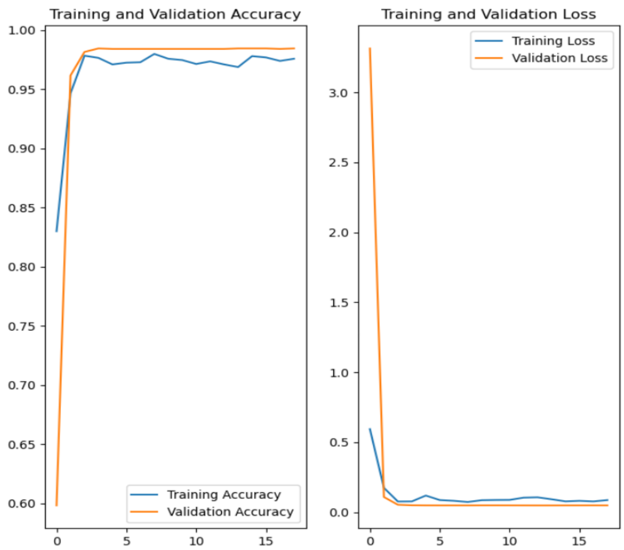


Figure 3. Epochs vs Accuracy Plot and Epochs vs Loss Plot

The ResNet50 model attained an impressive overall accuracy of 98% on the dataset. Figure 4 shows the prediction results of the ResNet-50 model. Upon analysing the classification report, it becomes evident that the model achieved remarkable precision, recall, and F1 scores across all classes. Notably, classes 0 and 4 exhibited perfect precision, recall, and F1 scores, while classes 1, 2, and 5 demonstrated high precision and recall. Although class 3 displayed slightly lower precision, recall, and F1 scores compared to the other classes, the values remained considerably high.

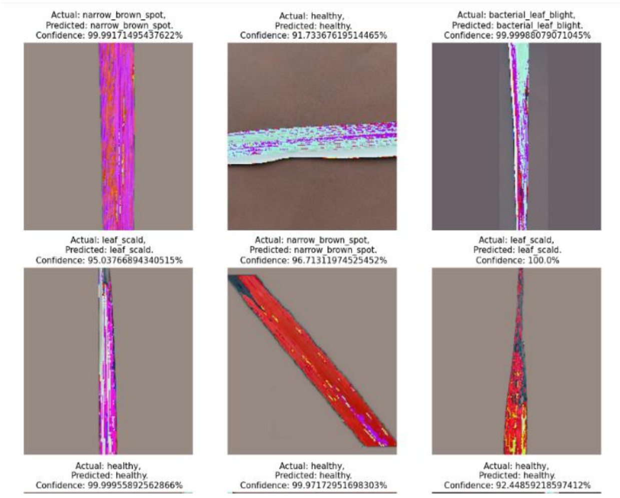


Figure 4. Prediction results of the ResNet-50 model

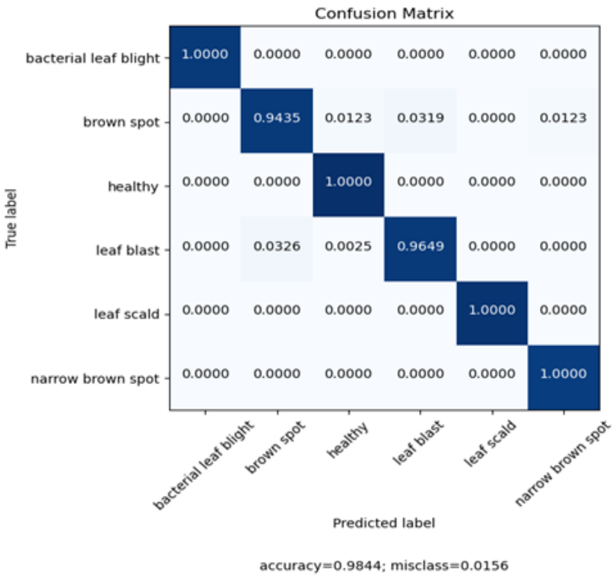


Figure 5. Confusion matrix of ResNet50 for different rice disease identification

IV. COMPARISON

To compare the ResNet-50 model we use VGG-16 and ResNet-101V2 models.

A. VGG-16

The classification report and confusion matrix of the VGG16 model as shown in Figure 6 indicates that it achieved high accuracy for most classes, but had lower precision and recall for the brown spot and narrow brown spot classes compared to the Resnet50 model. Specifically, the precision, recall, and F1-score of the VGG16 model for the brown spot and narrow brown spot classes were lower compared to the Resnet50 model. The VGG16 model achieved an accuracy of 92% on the dataset.

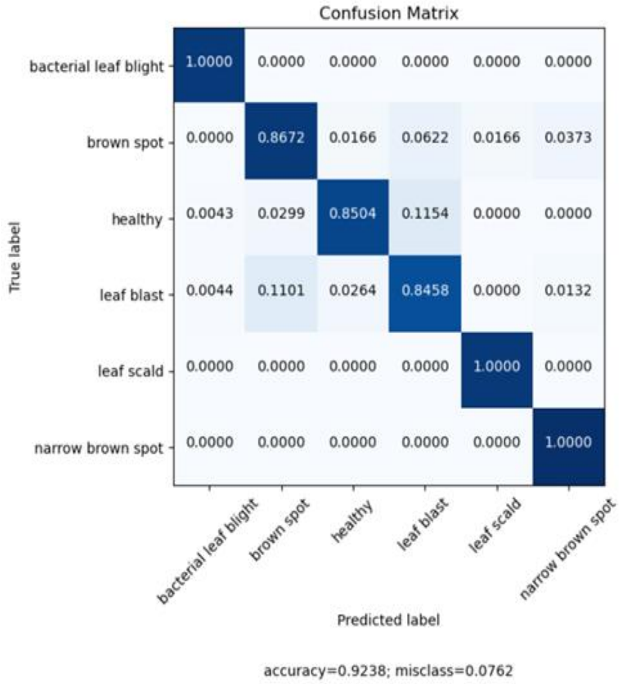


Figure 6. Confusion matrix of VGG16

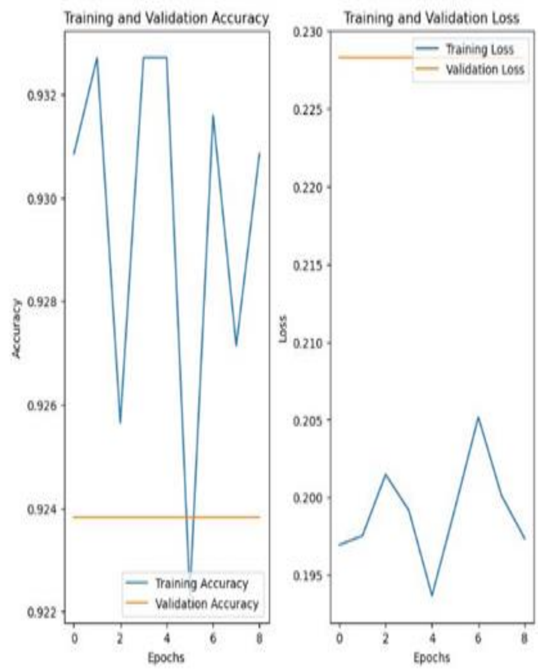


Figure 7. Epochs vs Accuracy Plot and Epochs vs Loss Plot of VGG16

B. ResNet-101V2

The classification report and confusion matrix of the Resnet101v2 model as shown in Figure 8 indicates that it achieved high precision and recall for all classes and had higher accuracy than the VGG16 model. Specifically, the precision, recall, and F1-score of the Resnet101v2 model for all classes were high, with no significant difference between the classes. The Resnet101v2 model achieved an accuracy of 93% on the dataset.

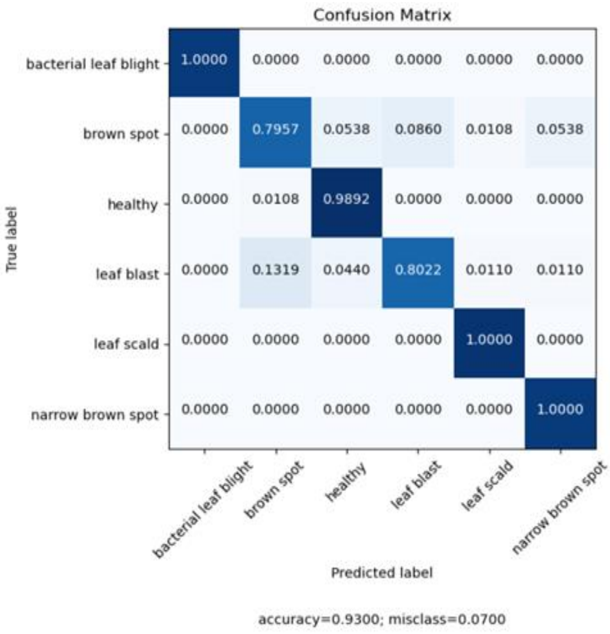


Figure 8. Confusion matrix of ResNet101V2

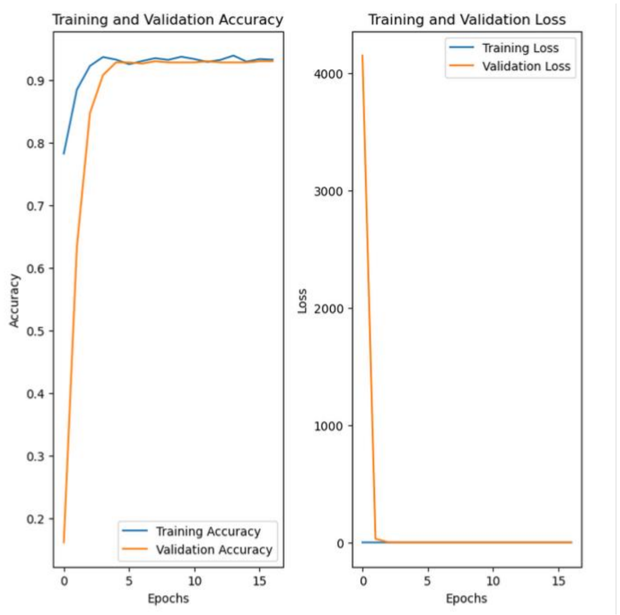


Figure 9. Epochs vs Accuracy Plot and Epochs vs Loss Plot of ResNet101V2

C. Summary

In conclusion, the Resnet-50 model achieved the highest validation accuracy and lowest validation loss, followed by the VGG-16, and Resnet-101v2 models. Overall, the comparison of the above models suggests that the Resnet-50 model is a strong performer for detecting paddy leaf disease, with high precision, recall, f1-score, and accuracy. To summarize, the findings of this study showcase the efficacy of the ResNet-50 model in accurately identifying various types of paddy leaf diseases. Below are comprehensive tables that present a detailed comparison of different models for the classification of diverse paddy leaf diseases.

Table 1. Comparison of different CNN models for bacterial leaf blight prediction

Model	Precision	Recall	F1-score
ResNet50	1.00	1.00	1.00
VGG16	0.99	1.00	1.00
ResNet101V2	1.00	1.00	1.00

According to Table 1, all three models exhibited exceptional performance in predicting bacterial leaf blight, with high precision, recall, and F1-scores. ResNet50 achieved perfect precision, recall, and F1-score values of 1.00, indicating that it accurately identified all instances of bacterial leaf blight without any false positives or false negatives. VGG16 and ResNet101V2 also achieved outstanding results, with precision values of 0.99 and 1.00, recall values of 1.00, and F1-scores of 1.00. These findings suggest that the CNN models, especially ResNet50, VGG16, and ResNet101V2, are highly effective in the prediction of bacterial leaf blight.

Table 2. Comparison of different CNN models for brown spot prediction

Model	Precision	Recall	F1-score
ResNet50	0.97	0.94	0.96
VGG16	0.87	0.87	0.87
ResNet101V2	0.85	0.80	0.82

Table 2 presents a comprehensive comparison of three CNN models (ResNet50, VGG16, and ResNet101V2) in terms of their performance in predicting brown spot. The evaluation was based on precision, recall, and F1-score metrics. ResNet50 achieved the highest precision of 0.97, indicating its ability to accurately identify instances of brown spot. The recall value of 0.94 suggests that ResNet50 effectively captured a significant portion of actual brown spot cases. The F1-score of 0.96 reflects a balanced performance in terms of precision and recall. On the other hand, VGG16 and ResNet101V2 exhibited lower precision, recall, and F1-score values compared to ResNet50, with VGG16 scoring 0.87 and ResNet101V2 scoring 0.85, 0.80, and 0.82, respectively.

In summary, ResNet50 outperformed the other models, demonstrating its potential for accurate brown spot prediction.

Table 3. Comparison of different CNN models for healthy prediction

Model	Precision	Recall	F1-score
ResNet50	0.99	1.00	0.99
VGG16	0.95	0.85	0.90
ResNet101V2	0.91	0.99	0.95

Table 3 presents a comparison of three CNN models (ResNet50, VGG16, and ResNet101V2) for predicting healthy instances. Precision, recall, and F1-measure metrics were used to assess their performance. ResNet50 achieved a high precision of 0.99, a recall value of 1.00, and an F1-measure of 0.99, indicating strong overall performance. VGG16 obtained a recall of 0.85, a precision of 0.95, and an F1-measure of 0.90, showing slightly lower accuracy than ResNet50. ResNet101V2 had a precision value of 0.91, a recall value of 0.99, and an F1-measure of 0.95, demonstrating high accuracy with a balanced precision-recall trade-off. In conclusion, all three models performed well in predicting healthy instances, with ResNet50 achieving the highest precision and recall.

Table 4. Comparison of different CNN models for leaf blast prediction

Model	Precision	Recall	F1-score
ResNet50	0.97	0.96	0.97
VGG16	0.82	0.85	0.83
ResNet101V2	0.90	0.80	0.85

Table 4 presents a comparison of three CNN models (ResNet50, VGG16, and ResNet101V2) for predicting leaf blast. Precision, recall, and F1-measure metrics were used to evaluate their performance. ResNet50 achieved a precision of 0.97 and a recall of 0.96, resulting in an F1-measure of 0.97, indicating strong overall performance in classifying leaf blast instances. VGG16 had a precision of 0.82 and a recall of 0.85, yielding an F1-measure of 0.83, indicating lower accuracy compared to ResNet50 in identifying leaf blast instances. ResNet101V2 achieved a precision of 0.90 and a recall of 0.80, resulting in an F1-measure of 0.85, demonstrating high accuracy with a balanced precision-recall trade-off. In conclusion, ResNet50 showed the highest performance among the three models for leaf blast prediction, highlighting its potential for accurate classification.

Table 5. Comparison of different CNN models for leaf scald prediction

Model	Precision	Recall	F1-score
ResNet50	1.00	1.00	1.00
VGG16	0.98	1.00	0.99
ResNet101V2	0.98	1.00	0.99

Table 5 presents a comparison of three CNN models, ResNet50, VGG16, and ResNet101V2, for predicting leaf scald. Precision, recall, and F1-score metrics were used to assess their performance. ResNet50 achieved a perfect precision, recall, and F1-score of 1.00, indicating flawless accuracy in correctly classifying leaf scald instances. Both VGG16 and ResNet101V2 also achieved excellent results, with precision values of 0.98, recall values of 1.00, and F1-scores of 0.99. These findings highlight the effectiveness of the CNN models, particularly ResNet50, VGG16, and ResNet101V2, in accurately predicting leaf scald.

Table 6. Comparison of different CNN models for narrow brown spot prediction

Model	Precision	Recall	F1-score
ResNet50	0.99	1.00	0.99
VGG16	0.95	1.00	0.97
ResNet101V2	0.94	1.00	0.97

Table 6 provides a comparative analysis of three CNN models (ResNet50, VGG16, and ResNet101V2) for predicting narrow brown spot. Precision, recall, and F1-score were utilized as evaluation metrics to assess their performance. ResNet50 exhibited a notable precision of 0.99, indicating strong accuracy in correctly identifying instances of narrow brown spot. The recall value of 1.00 suggests that ResNet50 successfully captured all actual narrow brown spot cases. An F1-score of 0.99 indicates a harmonious balance between precision and recall, demonstrating the model's overall robust performance. Likewise, VGG16 achieved a precision of 0.95, recall of 1.00, and an F1-score of 0.97, showcasing its high accuracy in classifying narrow brown spot instances. ResNet101V2 achieved a precision of 0.94, recall of 1.00, and an F1-score of 0.97, maintaining a strong performance, albeit with a slightly lower precision compared to ResNet50 and VGG16.In summary, all three models demonstrated strong performance in predicting narrow brown spot, with ResNet50 achieving the highest precision. These CNN models hold promise for accurate classification of narrow brown spot and can contribute to effective plant disease management. However, further research and validation are necessary to evaluate their performance across diverse datasets and environmental conditions.

V. CONCLUSION

In conclusion, our study demonstrates that the ResNet-50 deep learning model achieves an impressive accuracy of 98% in accurately detecting and classifying paddy leaf diseases. Comparatively, the VGG16 and ResNet101v2 models achieved accuracies of 92% and 93%, respectively. To ensure reliable results and generalizability, we carefully considered various factors such as dataset balance, splitting ratio, layer configurations, and data augmentation. While ResNet-50 was the primary focus of our study, future research could explore alternative CNN models such as VGG-19, EfficientNet and DenseNet, which hold promise for paddy leaf disease classification.

REFERENCES

[1] A. A. Joshi and B. D. Jadhav, "Monitoring and controlling rice diseases using Image processing techniques," 2016 International Conference on Computing, Analytics and Security Trends (CAST), Pune, India, 2016, pp. 471-476, doi: 10.1109/CAST.2016.7915015

[2] Krishnamoorthy, N. & Parameswari, V. (2021). “Rice Leaf Disease Detection Via Deep Neural Networks with Transfer Learning For Early Identification”. 32. 1087-1097.

[3] Latif, G.; Abdelhamid, S.E.; Mallouhy, R.E.; Alghazo, J.; Kazimi, Z.A. “Deep Learning Utilization in Agriculture: Detection of Rice Plant Diseases Using an Improved CNN Model”. Plants 2022, 11, 2230. https://doi.org/10.3390/plants11172230

[4] Osim Kumar Pal. “Identification Of Paddy Leaf Diseases Using A Supervised Neural Network”. 2021 16th International Conference on Emerging Technologies (ICET)

[5] Narendra Pal Singh Rathore.; Dr. Lalji Prasad. “Automatic Rice Plant Disease Recognition And Identification Using Convolutional Neural Network”. Journal Of Critical Reviews Issn- 2394-5125 Vol 7, Issue 15, 2020

[6] Badage, Anuradha. "Crop disease detection using machine learning: Indian agriculture." Int. Res. J. Eng. Technol.(IRJET) 5, no. 9 (2018): 866-869.

[7] R Swathika; S Srinidhi.; N Radha; Sowmya.“Disease Identification In Paddy Leaves Using Cnn Based Deep Learning”. 2021 Third International Conference On Intelligent Communication Technologies And Virtual Mobile Networks (Icicv)

[8] Islam, Md & Shuvo, Md & Shamsojjaman, Muhammad & Hasan, Shazid & Hossain, Md & Khatun, Tania. (2021). An Automated Convolutional Neural Network Based Approach for Paddy Leaf Disease Detection. International Journal of Advanced Computer Science and Applications. 12. 10.14569/IJACSA.2021.0120134.

[9] O. K. Pal, "Identification of Paddy Leaf Diseases Using a Supervised Neural Network," 2021 16th International Conference on Emerging Technologies (ICET), Islamabad, Pakistan, 2021, pp. 1-4, doi:10.1109/ICET54505.2021.9689788.

[10] Moparthi, N. R., Bhattacharyya, D., Balakrishna, G., & Prashanth, J. S. (2021). Paddy Leaf Disease Detection using CNN. NVEO-NATURAL VOLATILES & ESSENTIAL OILS Journal| NVEO, 800-806.

[11] Hossain, Syed & Tanjil, Md Monjur Morshed & Ali, Mohammed & Islam, Mohammad & Islam, Md & Mobassirin, Sabrina & Sarker, Iqbal & Islam, S. M. Riazul. (2021). Rice Leaf Diseases Recognition Using Convolutional Neural Networks. 10.1007/978-3-030-65390-3_23.

[12] Rahman, Rafeed & Arko, Preetom & Ali, Mohammed Eunus & Khan, Mohammad & Apon, Sajid Hasan & Nowrin, Farzana & Wasif, Abu. (2020). Identification and recognition of rice diseases and pests using convolutional neural networks. Biosystems Engineering. 194. 112-120. 10.1016/j.biosystemseng.2020.03.020.

[13] Lu, Yang & Yi, Shujuan & Zeng, Nianyin & Liu, Yurong & Zhang, Yong. (2017). Identification of Rice Diseases using Deep Convolutional Neural Networks. Neurocomputing. 267. 10.1016/j.neucom.2017.06.023.

[14] K. Ahmed, T. R. Shahidi, S. M. Irfanul Alam and S. Momen, "Rice Leaf Disease Detection Using Machine Learning Techniques," 2019 International Conference on Sustainable Technologies for Industry 4.0 (STI), Dhaka, Bangladesh, 2019, pp. 1-5, doi: 10.1109/STI47673.2019.9068096.

[15] Chen, Junde & Zhang, Defu & Nanehkaran, Yaser & Li, Dele. (2020). Detection of rice plant diseases based on deep transfer learning. Journal of the Science of Food and Agriculture. 100. 10.1002/jsfa.10365.

[16] S. Mathulaprangsan, K. Lanthong, D. Jetpipattanapong, S. Sateanpattanakul and S. Patarapuwadol, "Rice Diseases Recognition Using Effective Deep Learning Models," 2020 Joint International Conference on Digital Arts, Media and Technology with ECTI Northern Section Conference on Electrical, Electronics, Computer and Telecommunications Engineering (ECTI DAMT & NCON), Pattaya, Thailand, 2020, pp. 386-389, doi: 10.1109/ECTIDAMTNCON48261.2020.9090709.

[17] H. Ajra, M. K. Nahar, L. Sarkar and M. S. Islam, "Disease Detection of Plant Leaf using Image Processing and CNN with Preventive Measures," 2020 Emerging Technology in Computing, Communication and Electronics (ETCCE), Bangladesh, 2020, pp. 1-6, doi: 10.1109/ETCCE51779.2020.9350890.

[18] A. K and A. S. Singh, "Detection of Paddy Crops Diseases and Early Diagnosis Using Faster Regional Convolutional Neural Networks," 2021 International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE), Greater Noida, India, 2021, pp. 898-902, doi: 10.1109/ICACITE51222.2021.9404759.

[19] G. Sambasivam and Geoffrey Duncan Opiyo. (2020). A predictive machine learning application in agriculture: Cassava disease detection and classification with imbalanced dataset using convolutional neural networks. Egyptian Informatics Journal. 22. 10.1016/j.eij.2020.02.007.

[20] Ruoling Deng, Ming Tao, Hang Xing, Xiuli Yang, Chuang Liu, Kaifeng Liao and Long Qi. (2021). Automatic Diagnosis of Rice Diseases Using Deep Learning. Frontiers in Plant Science. 12. 10.3389/fpls.2021.701038.

[21] Ade, F. Rice Leaf Diseases Dataset. Available online: https://www.kaggle.com/datasets/adefiqri12/riceleafsv3