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Optimizing Rice Health: A Comparative Evaluation of Pretrained and Custom Convolutional Neural Networks for Disease Recognition

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Abstract: The most commonly used staple in the world, rice, is integral to daily living and working. Among diseases that attack rice plants, bacterial leaf blight, blast, brown spot, and false smut are the diseases affecting both the agricultural productivity and the quality of life of the people relying on it. Pesticides that are used in large quantities to treat these diseases are harmful to human health and disturb the natural balance. This study focuses on an automated machine learning-based approach that applies image processing techniques for accurate detection and classification of common rice leaf diseases. Convolutional neural networks were employed for high-accuracy classification, given that the processing, such as feature identification and noise reduction, was carried out within preprocessing phases. Our proposed model performed better compared to traditional deep learning architectures with an accuracy of 97.68% and precision, recall, and F1-score of 98%. In addition, we further examined the model using explainable AI. The results provide a cost-effective, scalable solution for early disease diagnosis with the ability to enable management to reduce crop loss. This study underscores the transformative potential of AI-powered precision agriculture technology in revolutionizing sustainable agriculture practices and boosting food security.

Keywords: custom model, pretrained model, rice leaf, explainable AI (XAI)

1. Introduction

Rice is one of the staple food sources of more than 50% of the global population, and its production is a crucial component for the world's food security [1]. However, diseases such as bacterial blight, brown spot, and blast can significantly reduce production and quality. Formerly, manual inspection was the reliance of farmers to identify these diseases, as other procedures are expensive, time-consuming, and can also have false positives. Disease detection is important as late detection could lead to substantial agricultural losses. Nowadays, advance in technology offers the possibility of automated solutions with the use of computerized vision and neural networks (NNs), which allow the rapid and precise diagnosis of rice leaf diseases. Plant disease identification is considered an image classification problem; deep learning models, in particular deep NNs, are shown to be very effective in image analysis of leaf images, feature extraction, and disease classification [2]. However, when IoT devices are integrated with AI-based methods and mobile applications, it boosts accessibility even more for farmers. These technological solutions can help cut production costs, encourage sustainable agricultural practices, and do away with the need to use chemical pesticides. This project intends to develop an efficient automated rice leaf disease detection system for optimizing the system of early detection, for improving crop health and agricultural production. The growing necessity for the prevention of crop losses and food security was a motivation behind this study. Conventional detection methods are ineffective, which in turn leads to late treatment and low yields. In addition to this, an intelligent, accurate, and efficient disease-detection system is critically needed, which, if deployed appropriately, can guide the proper decision-making of farmers at the right time. The project tries to use the development of AI, computer vision, and deep learning to construct an intelligent detection model to offer early disease prediction and assist the farmer in using cost-effective tools to adjust the crop management or ensure a stable food supply. In the use of artificial intelligence in the classification of rice leaf disease, although it has achieved some success, there are a lot of gaps in research. Most of the research has been conducted under controlled conditions and simulations in the laboratory; therefore, it may not apply when deployed under real conditions in which leaves may overlap, there will be weather conditions, and changes in the light conditions [3]. The low dimensionality and local specificity of the available datasets provide no generality of models and thus, the need for extensive and diverse

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datasets covering different rice varieties and diseases [4]. Furthermore, some of the research works have not made any direct comparison between different models, that is, Random Forest/convolutional NN (CNN) and principal component analysis-extreme learning machine, on a single dataset, which therefore made it difficult to ascertain the most appropriate approach. Among them, most of the deep learning models are also computationally expensive, making them inaccessible for small-scale farmers and prompting the need for lightweight portable models that can work with low power devices [4 – 6]. In addition, most available systems only diagnose diseases once visible symptoms have occurred, missing opportunities for early intervention, which could help limit crop losses using predictive methods such as hyperspectral imaging. These limitations are constraints for a stronger, more practical machine learning solution that may be applied to identify rice leaf disease. This work breaks these limitations by learning a model that is competent at tackling a wider range of diseases, generalizes well to challenging cases such as overlapping leaves, is more explainable, and can learn from larger and more diverse datasets. We have trained state-of-the-art CNN-based deep learning models, as well as our proposed CNN model, and generated a comparison report so that one can select a suitable model for the considered tasks. By bridging these gaps, the research will generate an automated algorithm that is accurate and interpretable, and deployable in farm fields, and will enable farmers to minimize their economic losses and maximize rice productivity.

2. Literature Review

Some studies have focused on the application of deep learning, machine learning, and ensemble learning for rice leaf disease detection. In addition, multiple CNN-based architectures have been proposed, such as VGG-16 [7], KNN [8], DenseNet [9], and Inception-ResNet-V2 [10], which all obtain a high classification accuracy. To optimize the rice leaf disease classification, many studies have applied the image processing methods, such as segmentation and RGB to HSV conversion [7-10]. There is some research work that got comparative accuracy by integrating feature extraction algorithms and classical machine learning algorithms, such as SVM and XGBoost [11]. YOLOv5 [13] and YOLOv4 [12] are two recently published object detection algorithms that were applied in identifying rice leaf diseases on leaves with varying sizes. Despite these developments, there are still a number of shortcomings, such as the current architecture, the lack of different types of data, and the lack of explainable AIs (XAIs) for interpretability [14]. Recent studies have not sufficiently investigated novel loss functions, such as yet another novel object loss, YOLOv8, with EIoU and a-IoU loss functions, in order to obtain the best model performance [15]. Besides, some models, such as NuSVM [16], suffered from the lack of reliable validation accuracy, and hence, there is a need for additional stable feature extraction and classification approaches. Although these problems have recently been tackled by designing custom architectures based on the CNN [17] and deep models SqueezeNet [18], which have achieved more than 93.3% accuracy, there are still some problems with the limitations of datasets and environmental conditions. The major research gaps in rice leaf disease detection are the need for models having better generalization ability on different datasets, the poor application of XAI for interpretability, and the lack of research into optimization techniques. A number of studies have been carried out with both traditional machine learning and deep learning models for plant and rice disease detection, with different degrees of achievements in terms of accuracy. Islam et al. [19] used CNN-based architectures such as VGG16, ResNet50, and DenseNet121, with an accuracy of 91.63%. Similarly, Bharanidhara et al. [20] used a traditional k nearest neighbor (KNN) classifier with an accuracy of 90%, which indicates the good performance of the simpler model in some special scenarios. Tejaswini et al. [21] tried more than one CNN method, such as VGG16, VGG19, Xception, ResNet, custom 5- layer CNN with relatively less accuracy of 78.20% as compared to other works. In another work, Tariq et al. [22] extended VGG16 using Layer-wise Relevance Propagation in order to increase interpretability and obtained 94.67% accuracy. Souvik et al. [23] implemented pretrained models, namely ResNet50 and VGG16, with the highest accuracy of 95.49% and Chiranjit Pal et al. [24] incorporated ResNet50 and InceptionV3 along with a custom CNN model and obtained one of the highest reported accuracies of 96.8%. Likewise, Abasi et al. [25] tested a proposed CNN model, InceptionV3, and EfficientNetB2 to attain an accuracy index of 95.7%. At the same time, tests were also carried out by V. Sai et al. [26]. Multiple CNN-based models, validation of the convolutional network with LIME, best accuracy 91.60%. These results highlight the benefits of using pre-tasked CNNs and hybrid strategies compared to traditional approaches for plant disease detection.

This research is able to move past the above shortcomings by extracting deep learning models, such as CNN, VGG16, and InceptionV3 based on the Kaggle “Rice Leaf Disease Detection” dataset with the aim of enhancing the classification accuracy and explainability. The research aims at early disease detection and sustainable rice cultivation practices. This research states that the deep learning technique, CNN, can be used for rice leaf disease detection to enhance the precision and accuracy of the detection relative to conventional human inspection. AI-based models will probably be able to discern trends in disease more accurately and accelerate crop diagnosis to allow better crop health management. Moreover, automatic detection of rice leaf diseases facilitates the early detection of this disease, which will reduce the crop loss and increase the efficacy of pesticides used for crop protection, thus helping to improve the agricultural production and sustainability. Leaf disease has tremendous impacts on both rice yield and food safety issues, and a rapid, precise, and large-scale detection system is greatly needed. Traditional manual inspection methods are generally time consuming, slow, and prone to human errors, and thus have poor effectiveness for real-time disease detection. Improvements in artificial intelligence, and in particular deep learning methods such as CNNs, have the potential to develop automated systems to produce accurate, real-time diagnoses. This project aims to help farmers make timely, informed decisions by using the AI-based models, thereby minimizing the wastage of pesticides, reducing crop losses, and ultimately leading to sustainable agriculture practices and food security. The comparison between existing research and our proposed methodology is presented in Table 1.

Table 1
The comparison between existing works

Author(s)	Technique	Algorithm used	Accuracy
Yuliany et al. [5]	CNN	CNN	77.33%
Wildah et al. [6]	Custom CNN	Custom CNN	98.86%
Ghosal et al. [7]	VGG16, CNN	VGG16, CNN	92.46%
Ramesh et al. [8]	KNN Model	KNN	92.6%
Chen et al. [9]	CNN-based models	DenseNet, Imagenet, Inception	98.63%
Islam et al. [10]	CNN Models	CNN based pretrained models	92.68%
Azim et al. [11]	Machine Learning	XGB, DT	86.58%

Author(s)	Technique	Algorithm used	Accuracy
Kiratiratanapruk et al. [12]	YOLO Techniques	YOLOv4, YOLOv8n, YOLOv8l, DI-NO-5scale Swin-L, and Co-DINO-5scale Swin-L models	93.20%
M. E. Haque et al. [13]	YOLOv5	YOLOv5	76% (mAP)
Ethiraj et al. [14]	DNet-SVM: XAI	DNet-SVM	53.81%
Trinh et al. [15]	Improved YOLOv8	YOLOv8 with EIoU & α-IoU loss	89.90%
Setiawan et al., [16]	Nu-SVM	Nu-SVM	52.12%-53.81%
Kulkarni et al. [17]	CNN	CNN	95%
A. Kaur, et al. [18]	SqueezeNet	VGG16, SqueezeNet, InceptionV3	93.3%
Islam et al. [19]	CNN Model	VGG16, ResNet50, and DenseNet121	91.67%
Bharanidharan et al. [20]	Machine learning models	KNN, RFC, LDAC, HGBC	90%
Tejaswini et al. [21]	CNN models	VGG16	58.4%
Souvik et al. [23]	CNN-based pre-trained model	ResNet50 and VGG16	95.49%
Chiranjit Pal et al. [24]	CNN-based pretrained model and custom CNN model	ResNet50, Inception V3, and proposed CNN model	96.8%
Ammar Kamal Abasi et al. [25]	CNN-based pretrained model and custom CNN model	Inception V3, EfficientNetB2, and Proposed CNN model	95.7%
V. Sai et al. [26]	CNN-based model	CNN-based model with LIME	91.60%
Our proposed model	CNN-based pretrained model and custom CNN model	EfficientNetB4, VGG19, VGG16, ResNet50, InceptionV3, and EfficientNetB0	97.68%

Note: CNN: convolutional neural network.

3. Methodology

Rice leaf disease detection representation has been greatly improved due to a number of image processing methods. Some studies have implemented CNN architectures, such as VGG-16, ResNet, DenseNet, and Inception, for better accuracy rates, but some have also used a combination of object detection models, such as YOLOv4 and YOLOv5. Previous researchers applied some traditional machine learning methods, such as SVM, XGBoost, and KNN, with different levels of success. Despite these advancements, there are some drawbacks, such as a lack of availability of XAI methods for the majority of the studies, uncertainty in the environment, as well as access to the dataset. Our approach for "Rice Leaf Disease Detection" Kaggle dataset attempts to surpass these limitations by improving the interpretability as well as the accuracy, using CNN, VGG-16, and InceptionV3. Going forward, the research has to focus more on combining datasets to create more meaningful machine learning models, enhancing the structure of models, and applying XAI to make the models more accurate and more practically helpful. CNN: CNN is an artificial NN that is applied for processing and analyzing visual information, such as movies and images. CNNs have shown great capabilities in object recognition, classification, and image recognition. We used almost all of the deep learning models, such as EfficientNetB4, VGG19, VGG16, ResNet50, InceptionV3, and Xception, to make a good model for finding rice leaf disease. We suggest a new CNN model for classifying rice leaf diseases in addition to the pretrained models. This research utilized a labeled dataset comprising images of rice leaves affected by variousdiseases, sourced from Kaggle.

To enhance classification accuracy, we devised an innovative CNN architecture for the classification of rice leaf disease. Our model uses several convolution layers with batch normalization, max pooling, and ReLU activation to find important features. To find different types of diseases, a softmax activation layer was used with fully connected layers. A global average pooling layer was added to reduce overfitting. Changing some of the parameters, such as the number of filters, the sizes of the kernels, the dropout, and the optimizer, will make the architecture better. Transfer Learning: The top layers of the pretrained deep learning models are fine-tuned and trained on the rice leaf dataset. Hyperparameter tuning is done on both the suggested CNN and the pretrained models. This increases the learning rate, batch size, and number of epochs. We used a number of evaluation metrics, such as accuracy, precision, recall, and F1-score, to compare how well the models worked.

Comparison and Optimization: We compared how well the proposed CNN model worked with how well pretrained models, such as InceptionV3, VGG19, and EfficientNetB4, worked. To enhance classification accuracy, we aimed to investigate ensemble learning techniques to evaluate the efficacy of various models in detecting illness patterns. Lastly, the model has been improved, and the results of this study will be used as a guide for other studies on automatic crop disease detection for precision agriculture.

3.1. Pretrained CNN models

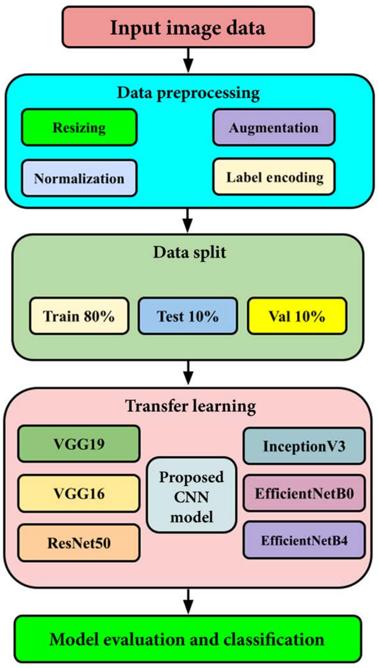
Pretrained models, such as EfficientNetB4, VGG19, VGG16, ResNet50, InceptionV3, and EfficientNetB0, are frequently used for image classification because of their potent feature extraction capabilities. These models undergo transfer learning, in which the final classification layers are adjusted using the rice leaf disease dataset, but not the first layers, which are in charge of obtaining fundamental characteristics, such as edges, textures, and shapes. Every model has special advantages, such as the following:

1) EfficientNetB4 and EfficientNetB0 maintain excellent accuracy while optimizing computational economy.
2) Although they need additional parameters, the deep networks VGG16 and VGG19 are capable of extracting extensive hierarchical information.
3) By employing factorized convolutions, InceptionV3 improves accuracy while lowering computing costs.
4) ResNet50 (Residual Network with 50 layers) is a deep CNN designed to overcome the vanishing gradient problem in very deep networks.

This research paper utilized models that have been pretrained as the base feature extractor for the diagnosis of rice leaf diseases, illustrated in Figure 1. All layers of this base model were set untrainable to retain the weights learned from ImageNet, thus retaining the features learned in pretraining and only training the custom classifier layers on the rice leaf dataset. The classifier includes a global average pooling layer, a dropout layer with a rate of 0.2, and a dense output layer of six neurons using a softmax activation for multiclass classification.

To prevent overfitting, early stopping was used during training by using a callback, which tracked the validation loss (val_loss) and stopped the training whenever there was no improvement over the past eight epochs. This ensured that the model training stopped at the optimal point, retaining the best generalization performance. By freezing the convolutional feature bases and only training the classifier layers with early stopping, the model achieved efficient training and effectively performed on the rice leaf disease dataset.

Figure 1
Proposed methodology flow diagram



Note: CNN: convolutional neural network.

Only the newly added top layers of the pretrained model are trained using the pictures of the damaged rice leaves from our dataset; the convolutional base module is not employed. Specifically, to preserve the pretrained weights acquired on ImageNet, the basic layers of the pretrained models are frozen. The photos of rice leaves were used to train just the top classifier layers, which are made up of the global average pooling layer, dropout layer, and dense output layer with six neurons and softmax activation. Using this approach, the pre-learned characteristics are preserved while the model learns to classify rice leaf diseases, which will not interfere with the usage of the dataset.

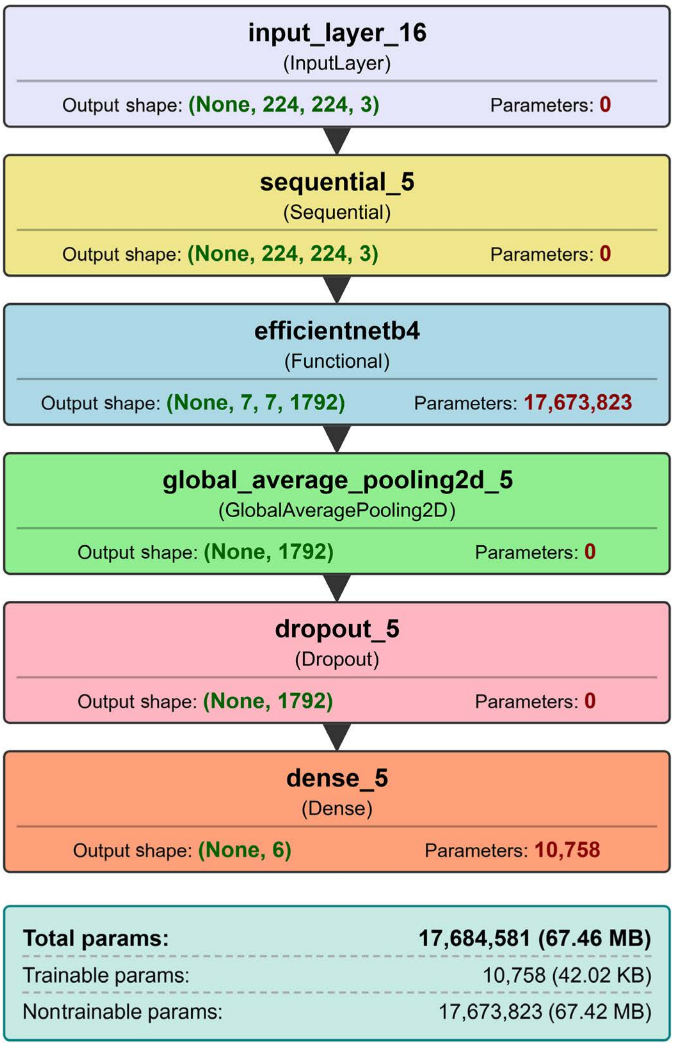
3.1.1. EfficientNetB4

EfficientNetB4 is a deep learning model employed in image classification that has both efficiency and accuracy balanced. EfficientNetB4 employs a compound scaling technique by fairly balancing all three dimensions, in contrast to conventional CNNs that scale width, depth, or resolution separately. As a result, the model can handle increasingly intricate image features without incurring undue computational costs. Each version (B0 to B7) is scaled in size and performance, starting with the baseline EfficientNet model. For applications requiring high accuracy but with acceptable training and inference speed, EfficientNetB4 is a particularly good compromise between small, fast models and very large, computationally intensive models. The network can learn more important features thanks to its architecture, which uses squeeze-and-excitation optimization with inverted residual blocks to cut out pointless calculations. In summary, EfficientNetB4 is a powerful model that balances efficiency and accuracy, making it appropriate for real-world image recognition applications. The EfficientNetB4 architecture is shown in Figure 2.

3.1.2. EfficientNetB0

EfficientNetB0 is the baseline model in the EfficientNet family. Its goal is to provide robust performance while preserving the speed and leanness of the model. Because of the compound scaling method used in its design, depth, width, and resolution scale in a correlated manner rather than improving one dimension. It makes the model strong enough without making it extremely large or slow. The network is built upon mobile inverted bottleneck blocks with squeeze-and-excitation layers so that it can preserve important image details while filtering out less important information. Owing to its compactness and efficiency, EfficientNetB0 can be utilized effectively in situations where the computing resource is constrained, that is, real-time systems or mobile applications. Even though EfficientNetB0 is the smallest model from the EfficientNet family, it provides tolerable accuracy relative to more complex and larger models, thereby making it an efficient alternative when speed and accuracy are both prime concerns. Figure 3 depicts the architecture of EfficientNetB0.

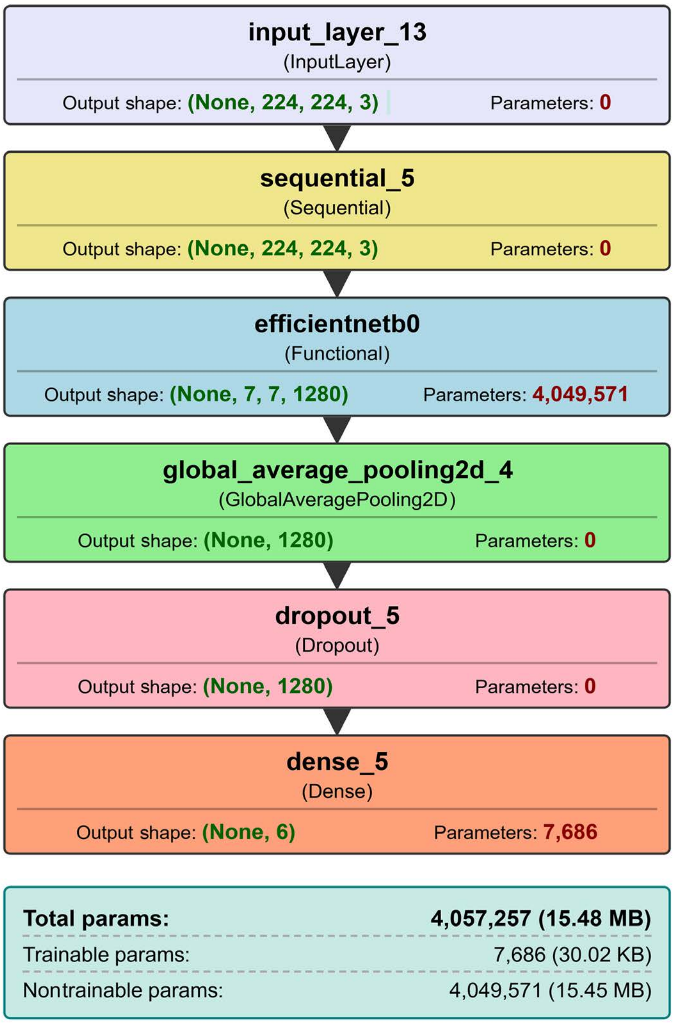
Figure 2
Architecture of EfficientNetB4



3.1.3. VGG19

VGG19 is a deep CNN that became popular due to its simplicity and strong performance in image recognition tasks. The model is built according to a simple design principle, stacking a sequence of a number of small 3 × 3 convolutional layers topped by one after another, instead of using larger kernels. This device allows the network to capture fine details and complex patterns without raising the number of parameters. VGG19 contains 19 weight layers, which are convolutional and fully connected layers, and in between them are pooling layers that gradually reduce spatial dimensions and highlight key features. One of its most salient strengths is that the regular architecture is simple to understand and extend to other problem types, such as classification, feature extraction, and transfer learning. However, VGG19 is very large in size and imposes very heavy computational requirements compared to newer models. However, it is still utilized as a baseline model for computer vision because of its ease of use, strong representational capability, and effectiveness on a vast range of different tasks. Figure 4 depicts the architecture of VGG19.

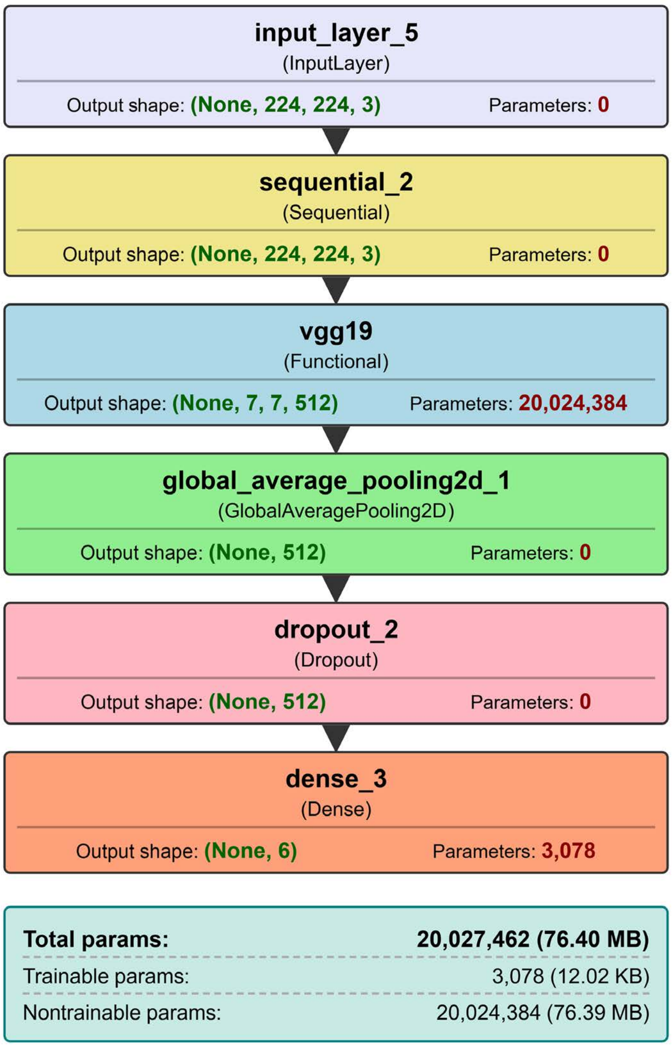
Figure 3
Architecture of EfficientNetB0



3.1.4. VGG16

VGG16 is a widely used CNN emphasizing depth as well as simplicity of architecture. It has 16 layers of weights, which are mainly made up of repeated stacks of 3 × 3 convolutional filters, used repeatedly to progressively capture more and more sophisticated patterns from input images. Pooling layers are inserted at intervals in cutting the dimensions when the retaining the layer's most important information, and the final fully connected layers handle classification. The uniform use of small convolutional kernels throughout the network helps it extract detailed features without requiring excessively large filters, making the model easier to generalize and adapt. Although VGG16 is computationally heavy and requires a lot of memory compared to newer models, it is more impactful in computer vision. Its clear architecture and strong performance have also made it a popularchoice for transfer learning, where pretrained features are reused for different image-based tasks. Figure 5 shows the architecture of VGG16.

Figure 4
Architecture of VGG19

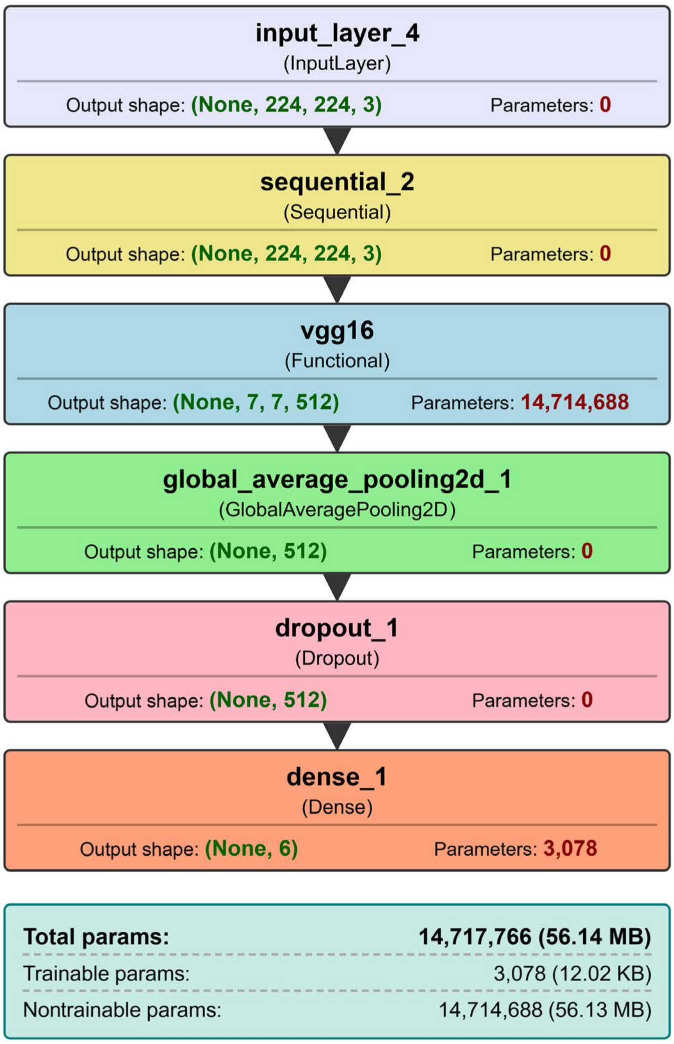


3.1.5. ResNet50

ResNet50 is a deep CNN that addresses the challenges of training very deep models by introducing the concept of residual learning. In traditional deep networks, adding more layers usually leads to vanishing gradients and lower accuracy, but ResNet50 mitigates this through the use of shortcut connections, or skip connections. Because of the connections, the network can transfer data directly between layers, making training easier and lowering the possibility of performance degradation as depth increases. Convolutional blocks and identity blocks that continuously use residual mapping are used to build the model's 50 layers. The network learns both high-level and low-level features more effectively thanks to this structure. In addition to its excellent classification performance, ResNet50 is widely used as the basis for object detection, segmentation, and other computer vision problems. Its ability to balance efficiency and depth makes it one of the most potent architectures for developing deep learning research. Figure 6 displays the ResNet50 architecture.

3.1.6. InceptionV3

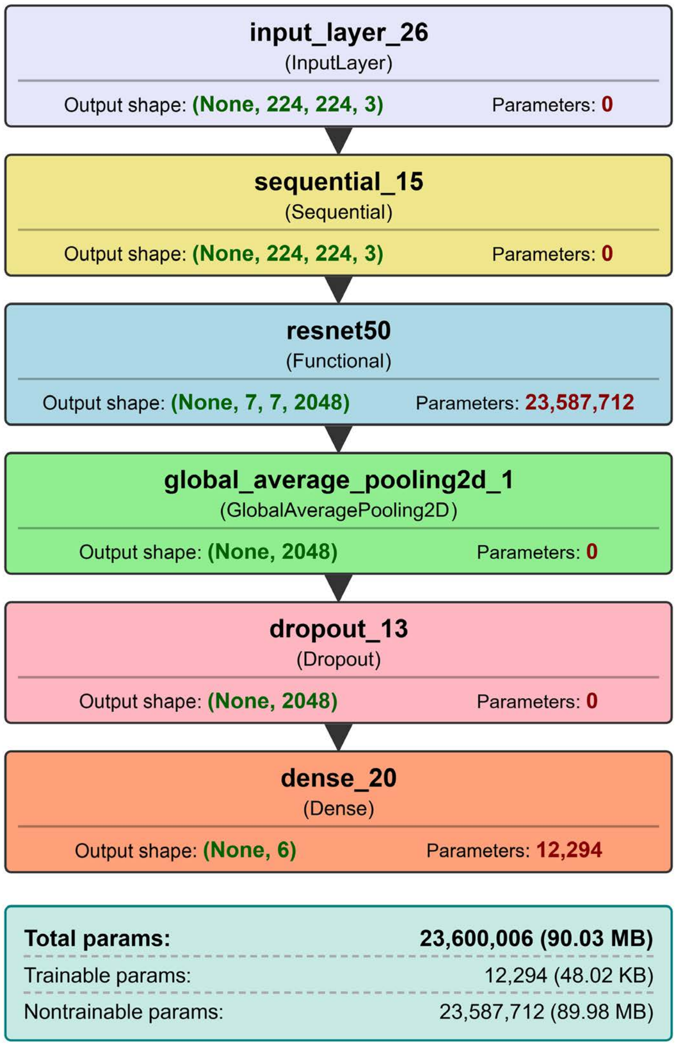
Figure 5
Architecture of VGG16



InceptionV3 is a deep CNN that uses Inception modules and aims to achieve high accuracy at a low computational cost. Instead of choosing a single filter size for convolutions, an independent module uses multiple sizes in parallel, such as 1 × 1, 3 × 3, and 5 × 5, and the outputs are summed. The network can learn more contextual information and finer details in the same layer thanks to this design. Additionally, InceptionV3 employs methods such as breaking down larger convolutions into smaller ones, employing batch normalization for training stabilization, and utilizing auxiliary classifiers to enhance gradient flow in deeper layers. As a 48-layer model, it effectively handles large-scale image classification problems because it strikes a balance between depth and efficacy. Because of its capacity to capture dense and multi-scale features without compromising model size or computational requirements, it has also emerged as a solid foundation for transfer learning and other vision tasks. The InceptionV3 architecture is shown in Figure 7.

3.1.7. Proposed custom CNN model

Figure 6
Architecture of ResNet50



We propose a specific CNN model to detect rice leaf disease in this study. It takes 224 × 224 × 3 input images and is optimized to extract and combine hierarchical features required for precise illness detection efficiently. It starts with an input layer, then there are four convolutional layers with progressively bigger filter sizes of 32, 64, 128, and 256, each of which applies ReLU activation to include non-linearity and detect intricate patterns. MaxPooling layers are applied after every convolution block to compress spatial dimensions without sacrificing essential features. The generated feature maps are then flattened and transferred to a fully connected dense layer of 256 units with ReLU activation. The technique suggested in Figure 8. To lessen the risk of overfitting, a Dropout layer with a rate of 0.2 is used. Six neurons using softmax activation make up the final output layer, which enables multiclass classification for six distinct rice leaf disease categories. Stable and effective learning is ensured by the model's construction using the Adam optimizer and categorical cross-entropy loss function. This special CNN is designed to address the problem of automated

Figure 7
Architecture of InceptionV3

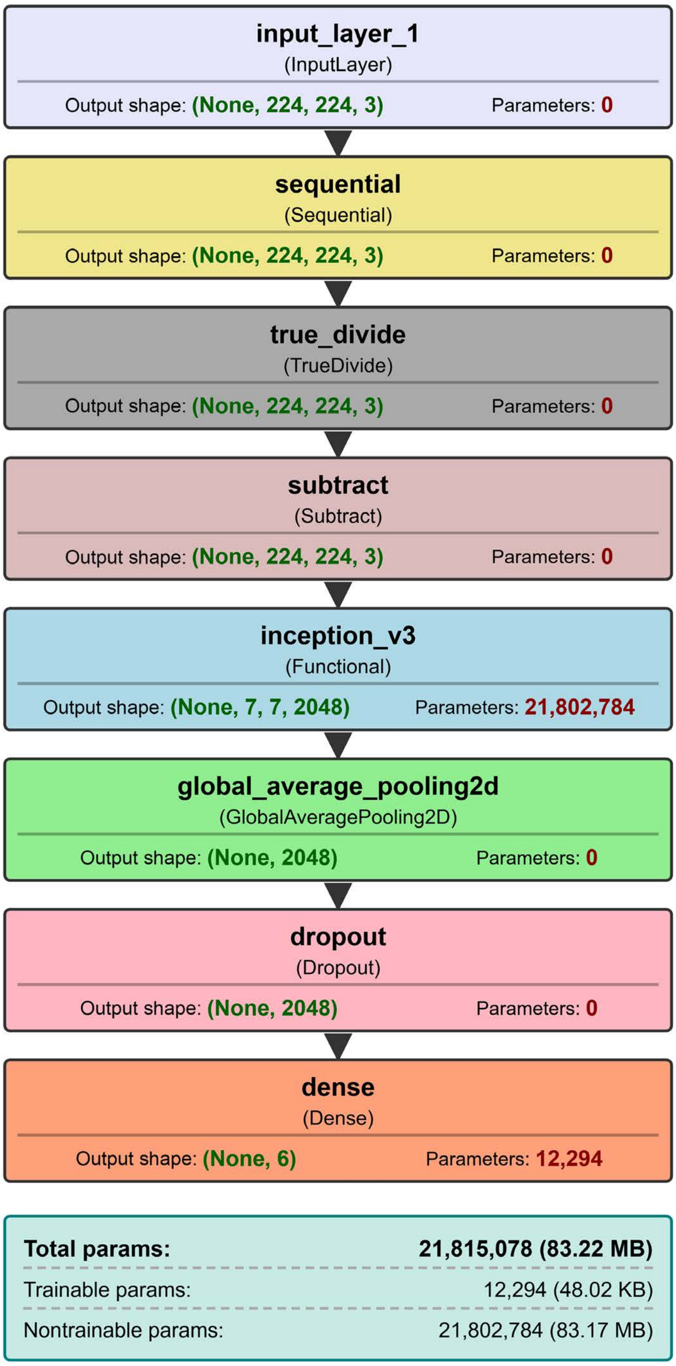
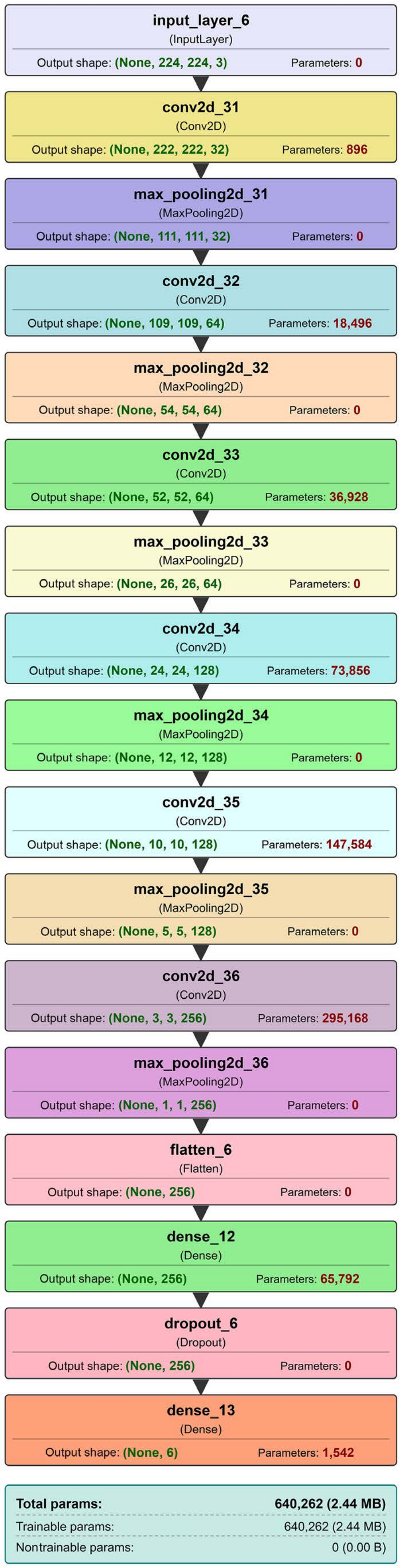


Figure 8
Proposed methodology



rice leaf disease identification by providing a portable, accurate, and comprehensible solution that is especially well-suited for agricultural image classification tasks. Figure 8 depicts the suggested process.

The suggested model presents a bespoke deep CNN architecture tailored for the detection of rice leaf diseases. As opposed to traditional pretrained networks, our model uses a number of max-pooling layers and convolutional layers with increasingly larger filter sizes (32 → 256), followed by fully connected layers with dropout to reduce overfitting. The network can effectively capture both detailed and abstract information thanks to this architecture, which is intended for feature extraction from images of rice leaves. The model architecture, which goes beyond simple model amalgamation or parameter adjustment, is customized for our particular dataset and includes layer depth, filter quantity, and dropout rate.

This study used a methodical trial-and-error approach to modify the hyperparameters of the suggested CNN model, namely learning rate, batch size, dropout rate, and optimizer selection. To identify the configuration that resulted in the highest validation accuracy while minimizing overfitting, a variety of combinations were empirically assessed. The batch size was chosen to optimize training efficiency and generalization, the learning rate was modified to guarantee stable convergence, and dropout rates were calibrated to minimize overfitting while maintaining model capacity. The Adam optimizer was selected because it continuously demonstrated superior convergence speed and overall accuracy for our dataset of rice leaf diseases when compared to other optimizers, such as SGD and RMSprop. This method made sure the model was properly calibrated for the particular properties of the data while preserving computational efficiency

4. Result Analysis

The dataset applied for this study was available on Kaggle (a popular platform of publicly available machine learning and deep learning datasets). Because it contains a large number of photos of various diseases occurring on rice leaves, the “RICE CROP DISEASES” dataset was selected. The data source is mentioned in the data availability section. Three thousand eight hundred and 29 images in the Rice Leaf Disease dataset were used to create six classes, namely, 636 images of Bacterial Leaf Blight, 646 images of Brown Spot, 653 images of Healthy Rice Leaf, 634 images of Leaf Blast, 628 images of Leaf Scald, and 632 images of Sheath Blight. The model bias was addressed by using the data augmentation techniques in the training. The data balancing technique consisted of random horizontal flip, random brightness adjusting (factor = 0.2), and random contrast adjusting (factor = 0.2). These transformations artificially introduced a certain amount of variability into the training data, which allowed for greatly improved generalization to real-world scenarios such as changing lighting and leaf orientation. A combination of augmentation techniques with a balanced dataset was able to enhance the classification performance of all disease classes of the model. These datasets guarantee wide and fair access to good-quality annotated images grouped by different types of diseases for proper model training and evaluation. Before being used in deep learning models, the photos were preprocessed and directly downloaded from Kaggle. Preprocessing was done using different methods such as scaling, normalization, and augmentation for better model functionality. A solid rice leaf disease recognition system should be built up with an open-domain dataset guaranteeing repeatability and comparability with previous research. Figure 9 shows the data sample on rice leaf disease.

4.1. Data preprocessing

In deep learning, “picture preprocessing” refers to a range of methods used to input images prior to their feeding into a NN. The objectives are to ensure high-quality input data, increase model performance, and improve training efficacy. In order to guarantee network architecture compliance, it is common practice to reduce photos to uniform dimensions. Normalization is frequently used to move pixel values to a predetermined range, such as 0 to 1 or −1 to 1, in order to increase training stability and decrease the dominance of individual characteristics. Mean subtraction and standardization enhance the data, improving feature extraction and reducing the impact of illumination variations by centering pixel values at zero and scaling them to unit variance. Rotation, flipping, translation, zooming, and cropping are examples of data augmentation techniques that artificially increase the dataset's variety, which strengthens the model's capacity for generalization. Filtering or denoising reduces noise, which enhances image clarity and promotes better learning. Edge detection techniques, such as the Canny or Sobel operators, highlight object boundaries, making feature extraction and segmentation easier, whereas techniques, such as histogram equalization, adjust pixel intensities to improve contrast and make visual patterns more visible. Making changes to color spaces, such as switching from RGB to grayscale or HSV, may improve performance or reduce processing requirements. Typically, the dataset was separated into three portions for training (80%), for testing (10%), and the rest for validation (10%). To ensure successful model training and accurate evaluation, preprocessing techniques, such as scaling, normalization, and augmentation, are used.

4.2. Experiment and evaluation

Usually, one or more performance measures are used to assess the performance of a machine learning or deep learning model. The ratio of accurate forecasts to total predictions is an indication of accuracy that may be directly measured by contrasting predicted and actual results. Despite its simplicity and widespread usage, accuracy is deceptive when used alone, particularly in cases when the data is uneven. Precision focuses on the percentage of correct positive predictions and indicates the model's degree of false positive mitigation, in contrast to recall, which is concerned with how effectively the model catches the real positives. The F1-score, which uses weighted harmonic averaging of the sensitivity and specificity of the prediction outcomes, is a useful way to measure model performance when the dataset is unbalanced [27–30]. To find any mistakes in the model, tools such as the confusion matrix provide a thorough examination of the false positives, false negatives, true positives, and true negatives. These metrics are often improved by hyperparameter tuning, which is the act of modifying hyperparameters such as learning rate, batch size, or number of network layers to optimize performance. By elucidating model predictions and offering the context for a particular outcome, a number of XAI approaches can assist practitioners in analyzing model behavior more quickly. When combined, these methods guarantee accurate models as well as an open and reliable decision-making process. The study's result is shown in Table 2.

Figure 9
Data sample of rice leaf disease

The efficacy of several deep learning models in identifying rice leaf illnesses was assessed using four principal metrics. The proposed model exhibited superior performance, with an accuracy of 97.68%, with Precision, Recall, and F1-score all at 98%, indicating its robust capacity to reliably differentiate between healthy and sick leaves. Among the pretrained architectures, EfficientNetB0 achieved remarkable results, with 93.83% accuracy and 94% across all assessment measures, underscoring the efficacy of its compound scaling methodology for feature extraction in this challenge. VGG16 and InceptionV3 demonstrated competitive but somewhat inferior performance, achieving accuracies of 87.91% and 87.66%, respectively, while sustaining balanced Precision and Recall near 88%, signifying dependable albeit less sophisticated detection skills in comparison to the EfficientNet models. VGG19 achieved an accuracy of 87.14%, demonstrating comparable metric values somewhat lower than those of VGG16. EfficientNetB4 attained an accuracy of 88.68%,

Table 2
The result analysis of the deep learning model

Algorithms	Accuracy	Precision	Recall	F1-score
VGG19	87.14	88	87	87
VGG16	87.91	88	88	88
ResNet50	83.03	83	83	83
EfficientNetB0	93.83	94	94	94
EfficientNetB4	88.68	89	89	89
InceptionV3	87.66	89	88	88
Proposed model	97.68	98	98	98

surpassing VGG and Inception networks, while remaining inferior to EfficientNetB0, indicating that model complexity and hyperparameter optimization considerably influence performance. ResNet50, although widely utilized in computer vision, achieved the lowest performance with an accuracy of 83.03% and matching Precision, Recall, and F1-score of 83%, suggesting that its residual connections were less adept at detecting nuanced patterns in rice leaf diseases. These results indicate that although conventional deep learning architectures exhibit commendable performance, the Proposed Model distinctly provides enhanced accuracy, resilience, and generalization in detecting rice leaf diseases. Figures 10, 11, 12, and 13 illustrate the confusion matrix, accuracy and loss curves, the classification report, and the GRAD-CAM of the proposed model, respectively, offering more insight into model performance.

5. Future Work

Future research can enhance the proposed rice leaf disease detection model by integrating larger and more diverse datasets sourced from various geographical regions, thereby improving the model's generalizability across different environments. Creating real-time detection apps for mobile devices or imaging systems

Figure 10
The confusion matrix of the proposed model

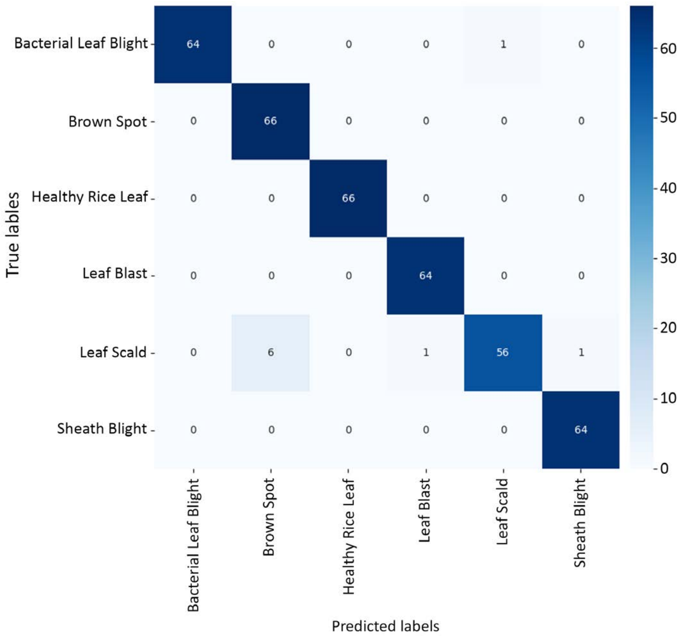


Figure 11
The accuracy and loss graph for the proposed model

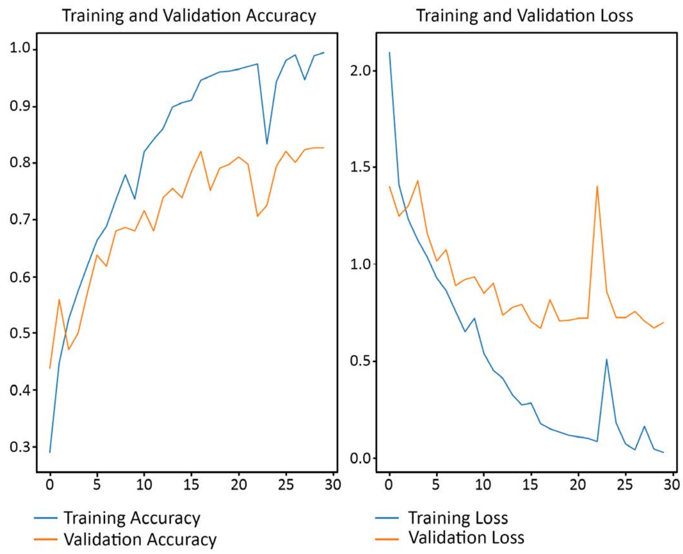


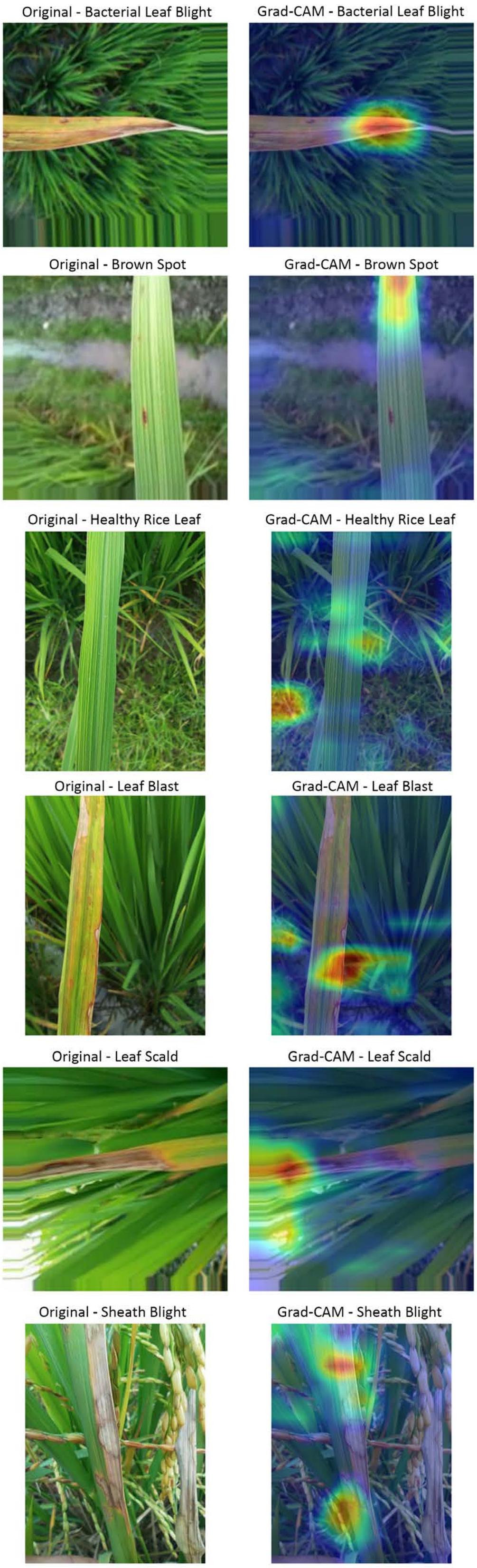
Figure 12
The classification report for proposed model

```
Classification Report:
                       precision    recall  f1-score   support

Bacterial Leaf Blight       1.00      0.98      0.99        65
           Brown Spot       0.92      1.00      0.96        66
    Healthy Rice Leaf       1.00      1.00      1.00        66
           Leaf Blast       0.98      1.00      0.99        64
           Leaf scald       0.98      0.88      0.93        64
        Sheath Blight       0.98      1.00      0.99        64

             accuracy                           0.98       389
            macro avg       0.98      0.98      0.98       389
         weighted avg       0.98      0.98      0.98       389
```

Figure 13
The GRAD CAM (XAI) for the proposed model



based on drones could help farmers in the field in a timely manner. Furthermore, by optimizing the model for low-resource devices using techniques such as quantization or pruning, it may be possible to lower computational requirements and enable wider deployment. By improving the interpretation of the model's predictions, XAI techniques would boost user trust. The system may be more advantageous for sustainable agriculture if its ability to assess the severity of the disease and recommend treatments is improved The simulation results show that the proposed UNet method of this research has main advantages for practical applications. In fact, in addition to having a basic and standardized architecture, the proposed method UNet with attention mechanism also has good accuracy. The results presented in the table show that the proposed method has the highest accuracy. Also, the proposed method is simulated on a standard dataset. However, this method still has limitations; one of the most important limitations of the proposed method is the lack of access to a large dataset. If this limitation is removed, it is possible to examine the advantages and disadvantages of the proposed method.

5. Conclusion and Future Works

The application of deep learning and image processing techniques has greatly improved the detection of diseases of rice leaves. Researchers have examined a range of approaches, including CNN architectures, such as VGG16, ResNet, DenseNet, and Inception, as well as object detection models, such as YOLOv4 and YOLOv5, with differing degrees of success. Conventional machine learning techniques, such as SVM, XGBoost, and KNN, have been used, but they have drawbacks, such as poor explainability, variable environmental conditions, and limited access to datasets. To improve interpretability and accuracy on the “Rice Leaf Disease Detection” Kaggle dataset, we employ CNNs, VGG16, and InceptionV3. To increase the accuracy and usefulness of rice disease detection systems for sustainable agriculture, future research must focus on incorporating larger datasets, improving model architectures, and applying explainable artificial intelligence techniques.

Recommendations

In future research, rice leaf illness classification is proposed to create larger and more diverse datasets to better reflect realworld environmental variations, enhancing deep learning model architectures for greater robustness and generalization, and utilizing XAI techniques to make model decisions more transparent and trustworthy for farmers and agricultural experts. While optimizing lightweight models would make deployment on mobile and edge devices easier for real-time field applications, incorporating ensemble methods that combine multiple models could further increase accuracy. These methods will improve the accuracy, comprehensibility, and utility of rice disease detection systems for sustainable agriculture.

Ethical Statement

None of the authors of this paper has conducted any research with humans or animals.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

The data that support the findings of this study are openly available in Kaggle at https://www.kaggle.com/datasets/anshulm257/rice-disease-dataset.

Author Contribution Statement

Aunik Hasan Mridul: Conceptualization, Methodology, Software, Validation, Writing – review & editing, Supervision, Project administration. **Jannatul Fardus Armin:** Conceptualization, Methodology, Validation, Data curation, Writing – original draft, Writing – review & editing. **Md. Abu Saleh:** Writing – original draft, Visualization. **Akash Das:** Formal analysis, Investigation, Data curation, Writing – original draft, Visualization. **Md. Mahidul Islam:** Methodology, Software, Formal analysis, Investigation, Writing – original draft, Writing – review & editing. **Sujan:** Formal analysis, Investigation. **G. M. Shakil:** Formal analysis, Investigation, Resources. **Md. Abdur Rakib:** Software, Resources.

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