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A smart agriculture solution for crop disease detection : A deep learning approach

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Abstract

Crop diseases can greatly affect crop yields, and early detection is thus important to reduce losses. Recently, different automatic plant disease recognition systems have been developed. This paper introduces four deep learning models—VGG16, EfficientNetB0, ResNet-50, and GoogleNet to recognize four rice diseases based on plant leaf images. The models were trained and tested using different public datasets, including the Rice Leaf Disease Image dataset in Mendeley. The Dense Layer model of VGG16 has an accuracy rate of 99.747%, while that of VGG16 2D-CNN is 99.916%. The Dense Layer model also recorded a validation loss of 1.3880 with a test accuracy of 27.004%, while the 2D-CNN EfficientNetB0 model has a validation loss of 1.3830 with the same test accuracy. ResNet-50 with Dense Layer decreased the validation loss to 0.8121 and had a test accuracy of 70.211%, whereas ResNet-50 2D-CNN achieved a validation loss of 0.7238 with a test accuracy of 69.789%. Lastly, the GoogleNet model with Dense Layer provided 99.916% accuracy, and the GoogleNet 2D-CNN model had 99.831% accuracy. The outcomes show that such sophisticated deep learning models diagnose rice diseases accurately, providing intelligent agriculture solutions for disease detection at the early stage. Farmers can be assisted by deploying AI-based systems to ensure optimal crop yields and quality. Overall, this research proves that plant disease diagnosis can be done highly effectively using AI-based approaches and presents a green solution to an important agricultural issue.

Subject Classification: *68T05, 68T07.*

Keywords: *VGG16, EfficientNetB0, ResNet-50, GoogleNet.*

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I. Introduction

The agriculture sector faces mounting challenges due to rising food demand, efficiency needs, and crop losses, with disease detection being a critical issue. Conventional methods are slow and expertise-dependent, prompting demand [4] for automated monitoring systems. Rice, the world's most consumed staple, is highly vulnerable to diseases that reduce yield and quality, causing global food security and economic concerns. Annual rice production declines by 37% due to diseases, disproportionately [12] affecting low-income regions through higher prices and reduced access. To address this, researchers are exploring computer vision and machine [7] learning for real-time rice disease detection, enabling early diagnosis and intervention. Techniques like image processing and CNNs (LeNet, AlexNet, GoogleNet [1], VGG, ResNet) extract features such as color, texture, and shape for accurate classification. VGG-16, with its deep architecture and 3×3 filters, is widely used but computationally intensive, while EfficientNet and ResNet offer scalable and gradient-stable alternatives. Data augmentation further enhances model performance by diversifying training datasets through rotations, scaling, and color shifts. Deep learning's hierarchical feature extraction makes it powerful for [5] crop diagnostics, reducing losses and improving sustainability. This research proposes a VGG-based rice leaf disease detection system, [3] adaptable to other crops, to support precision farming and strengthen global food security.

II. Literature Survey

Several studies have advanced plant disease detection using deep learning and computer vision. Rahman et al. [22] demonstrated imaging-based expert systems for sugar [8] beet leaf spot, achieving 95.48% accuracy with Faster R-CNN, reducing human dependency and time. Militante and Gerardo [6] applied deep learning to sugarcane disease detection using 13,842 images, reaching 95% accuracy and empowering farmers with early diagnosis. Chung et al. [17] investigated Bakanae disease in rice using SVM classifiers and genetic algorithms, achieving 87.9% precision, highlighting early detection's importance. Kamal et al. [19] introduced depth-wise separable convolutions, with Reduced MobileNet achieving 98.34% accuracy using fewer parameters, enabling real-time mobile applications. Chen, Zhang, and Nanehkaran [20] explored transfer learning with VGGNet and Inception, attaining 92% accuracy even with complex backgrounds, underscoring deep learning's reliability Barbedo [25] focused on lesion-based segmentation, improving accuracy by 12% compared to whole-leaf analysis, though requiring human input. Finally, Md Humaion Kabir Mehedi et al. applied EfficientNetV2L with LIME for transparent predictions, achieving 99.63% accuracy across 38 diseases in 14 plant species. Collectively, these works highlight the transformative role of CNNs, [23] transfer learning, and lightweight architectures in advancing automated, scalable, and precise plant disease diagnostics for sustainable agriculture [14]. The comparative performance of CNN-based models across different crops is summarized in Table 1, highlighting accuracies ranging from ~90% to ~99% depending on the dataset and architecture.

Table 1

Literature Review

Researcher(s)	**Year**	**Title of Paper**	**Classifier / Model**	**Accuracy**
Mahum et al. [2]	2022	A novel framework for potato leaf disease detection using an efficient deep learning model	Deep CNN	~95%
Ozden [10]	2021	Apple leaf disease detection and classification based on transfer learning	Transfer learning (CNN)	~98%
Saleem et al. [11]	2020	Image-based plant disease identification by deep learning meta-architectures	CNN meta-architectures (Inception, ResNet, DenseNet)	~99%
Haridasan, Thomas, and Raj [13]	2022	Deep learning system for paddy plant disease detection	CNN	~95%
Bashir, Rehman, and Bari [15]	2019	Detection and classification of rice diseases using textural features	Textural features + ML	~90%

Contd...

Singh and Misra [16]	2017	Detection of plant leaf diseases using segmentation and soft computing	Segmentation + soft computing	~92%
Chung et al. [17]	2016	Detecting Bakanae disease in rice seedlings by machine vision	SVM + genetic algorithms	87.9%
Yang et al. [18]	2023	Disease detection of rice leaf using improved detection transformer	Transformer-based CNN	~97%
Kamal et al. [19]	2019	Depthwise separable convolution architectures for plant disease classification	MobileNet, VGG	98.34%
Chen, Zhang, and Nanehkaran [20]	2020	Identifying plant diseases using deep transfer learning	VGGNet, Inception	92%
Adem, Ozguven and Altas [21]	2023	Sugar beet leaf disease classification using deep learning	Faster R-CNN	95.48%
Rahman et al. [22]	2022	Detection of tomato leaf diseases using image processing	CNN + image processing	~94%
Fayyaz et al. [24]	2022	Leaf blights detection and classification in large-scale applications	CNN	~96%
Barbedo [25]	2019	Plant disease identification from individual lesions and spots	CNN (lesion-based segmentation)	+12% vs whole-leaf (~75–87%)
Algani et al. [26]	2023	Leaf disease identification using optimized deep learning	Optimized CNN	~97%
Jia et al. [27]	2023	MobileNet-CA-YOLO for rice pests and diseases	YOLOv7 + MobileNetV3	~98%

Contd...

Ahmad et al. [28]	2020	Optimizing pretrained CNNs for tomato leaf disease detection	Pretrained CNN (ResNet, VGG)	~95%
Zamani et al. [29]	2022	Performance of ML and image processing in plant leaf disease detection	ML + image processing	~92%
Mehedi et al. [30]	2022	Plant Leaf Disease Detection using Transfer Learning and Explainable AI	EfficientNet-V2L + LIME	99.63%

III. Proposed approach

A. *VGG-CNN mode*l

The CNN model is a Convolutional Neural Network (CNN) used for image classification. It utilizes a pre-trained VGG16 model. The VGG16 model's dataset is frozen to prevent modification during training. The model architecture then adds 2D filters, both with a 3x3 size and a padding of 'same' to preserve the image dimensions. These layers use a ReLU activation function to introduce non-linearity to the model (as shown in Figure 1).

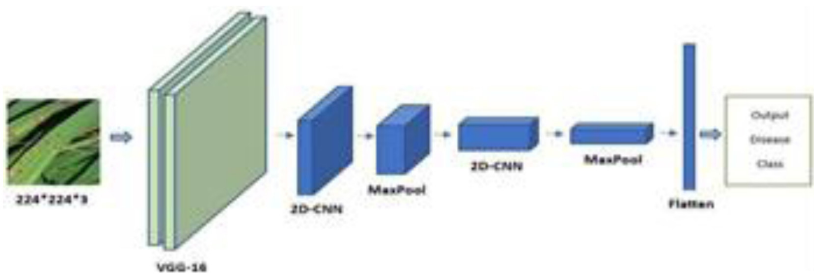

Figure 1

VGG-CNN crop disease identification

In deep learning, spatial dimension defines the width, height, and channels of input data, crucial in image recognition tasks. A grayscale image of 224×224 pixels has dimensions (224, 224, 1), while a color image has (224, 224, 3). Convolutional layers process 2D inputs, whereas fully connected layers handle 1D data. Larger spatial dimensions demand more computation and memory, slowing training. Techniques like downsampling

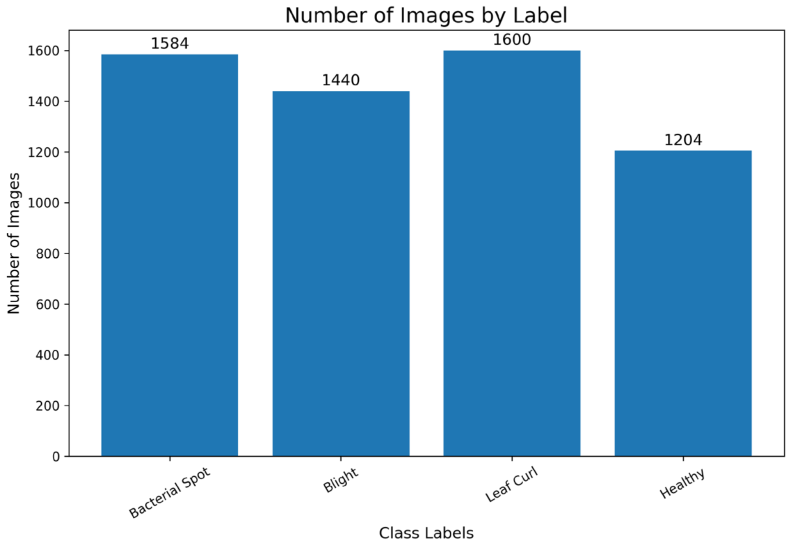

Figure 2

Number of images

or cropping reduce dimensions to improve efficiency, though at the cost of some information.

B. *Experimental evaluation*

The dataset contains 5932 TIFF file format images of diseased and healthy rice leaves, including categories such as Bacterial blight, Blast, Brown spots, and Tungro. Common diseases in plants as shown in Figure 6. The dataset is split into 80% for training (4747 images) and 20% for testing (As shown in Figure 2) (1185 images), as shown in Figure 3.

The images were likely captured using cameras or other imaging devices and have different resolutions, sizes, and colours. This split is a common practice in machine learning to ensure the model does not overfit the training data and can generalize well to new, unseen data. The training set is used to train a machine learning model to recognize and classify different types of rice leaf diseases. As shown in Figure 4 and 5 This involves using various techniques such as feature extraction to identify relevant features and patterns from the images, allowing the model to distinguish between healthy and diseased leaves. Once the model is trained, it is evaluated on the testing set to determine its accuracy and effectiveness in classifying the images. The testing set serves as a benchmark for the model's performance. If the model performs well on this set, it is considered to have good generalization capability and can be used to classify new, unseen images of rice leaves. Figure 3 illustrates the workflow in the study.

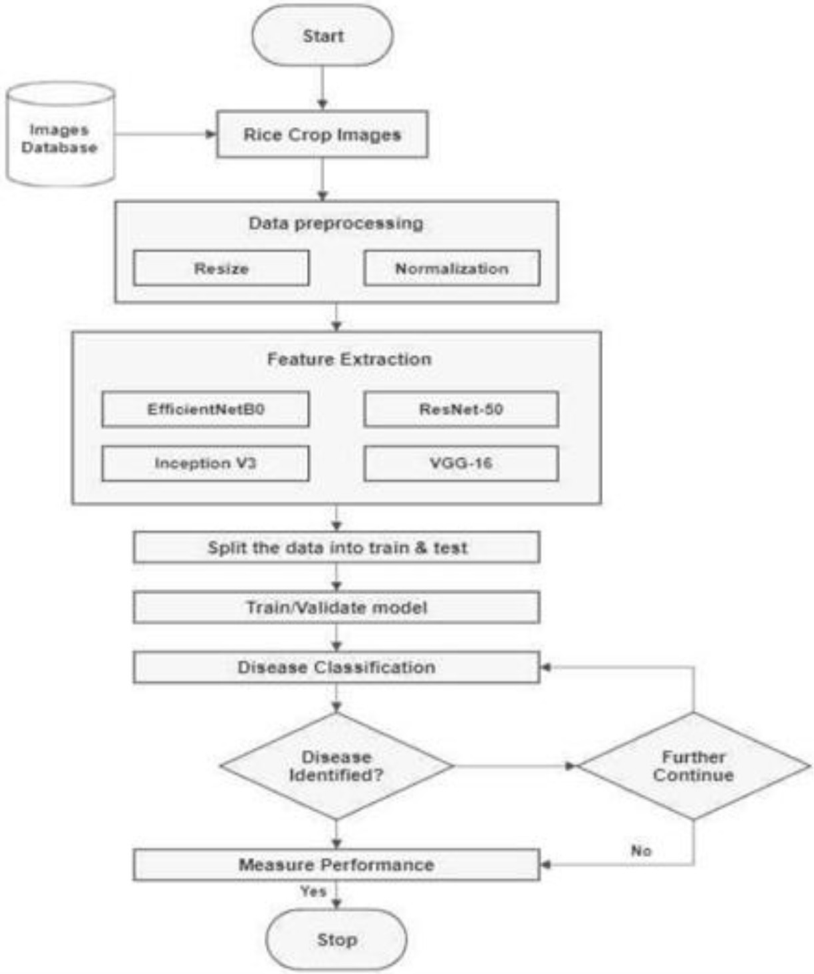

Figure 3
Work flow

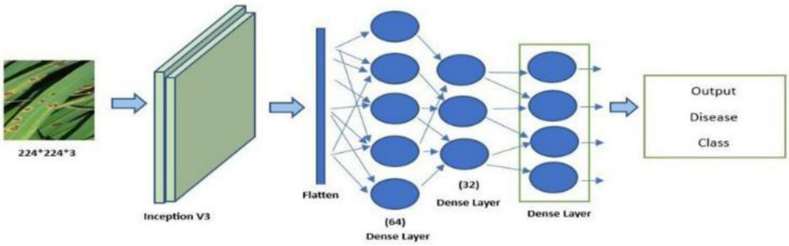

Figure 4

Dense Layer

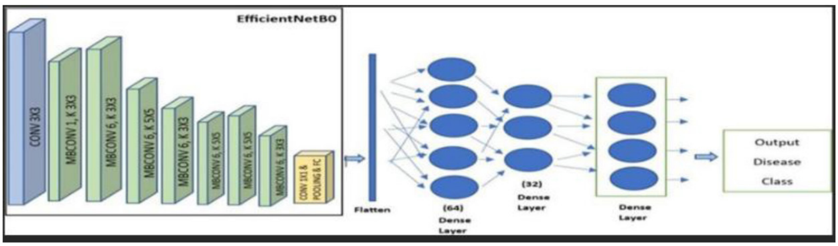

Figure 5

EfficientNetB0

Figure 6

Common diseases in plants

IV. Results and discussion

The tables reveals significant insights into the performance of various deep learning models for detecting rice diseases. The VGG16 models, both with Dense Layer and 2D-CNN configurations, demonstrated outstanding performance, achieving a remarkably low training loss (1.0585e-05), validation loss (0.0417), and a test accuracy of 99.41%. Similarly, the EfficientNetB0 with a Dense Layer shared identical results, indicating its robustness in handling this task. However, the EfficientNetB0 with the

2D-CNN configuration, although exhibiting slightly higher losses (training loss: 0.1023, validation loss: 0.0654), still maintained a commendable test accuracy of 98.63%. This suggests that the 2D-CNN approach in EfficientNetB0 is effective, albeit marginally less accurate than its Dense Layer counterpart. As shown in Figure 7 and 8. On the other hand, the ResNet-50 models showed considerable variation in their performance. The Dense Layer configuration had a relatively higher training loss (0.6619) and validation loss (0.7438) with a lower test accuracy of 67.09%. Conversely, the 2D-CNN version reduced both losses (training loss: 0.4040, validation loss: 0.5829) and achieved a notably better test accuracy of 78.57%. Lastly, the GoogleNet models displayed strong results, with the Dense Layer achieving a training loss of 0.0818, validation loss of 0.1018, and test accuracy of 98.65%. The detailed accuracy, training loss, and validation loss values for each model configuration are presented in Table 2, confirming the superior performance of VGG16 and EfficientNetB0 with Dense Layers. The 2D-CNN variant had slightly higher losses (training loss: 0.0954, validation loss: 0.0673) but a comparable test accuracy of 98.57%. To further validate classification robustness, F1-scores for each rice disease category are reported in Table 3, showing balanced performance across Bacterial Blight, Blast, Brown Spot, and Tungro. The analysis shows that deep learning models, particularly those with Dense Layer configurations, exhibit high effectiveness in diagnosing rice diseases. Recall values for each disease class are provided in Table 4, demonstrating that VGG and EfficientNetB0 models achieved consistent recall across categories. Implementing these models in real-world agricultural

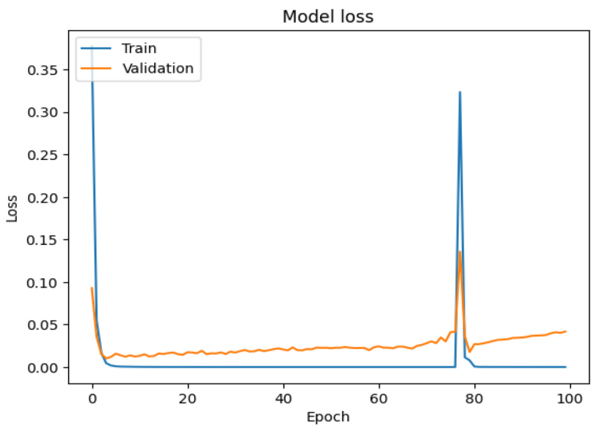

Figure 7

VGG 16 Loss Dense Layer

applications can significantly enhance early disease detection, ensuring optimal crop yields and quality. Specificity values for all models are summarized in Table 6, confirming that Dense Layer configurations generally provided better discrimination between diseased and healthy leaves. Precision scores, shown in Table 5, indicate that ResNet-50 models, despite lower accuracy, achieved relatively higher precision for certain disease classes. As shown in Figure 9 and 10.

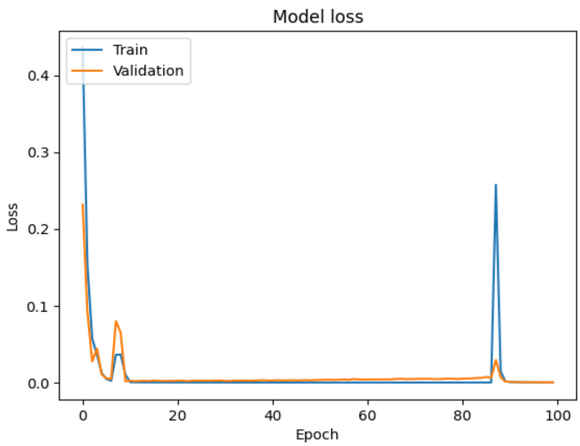

Figure 8

VGG 16 Loss CNN

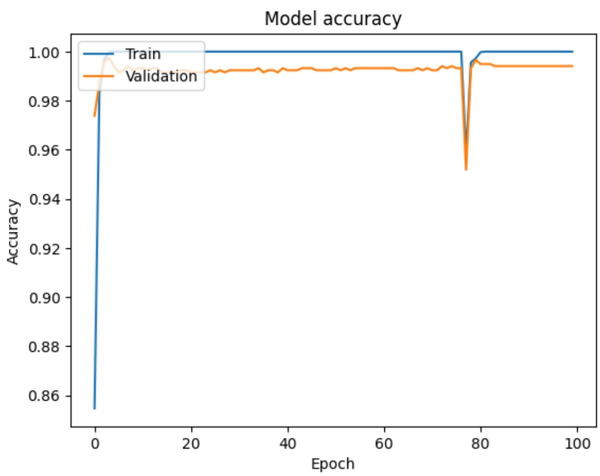

Figure 9

VGG 16 Accuracy Dense Laye

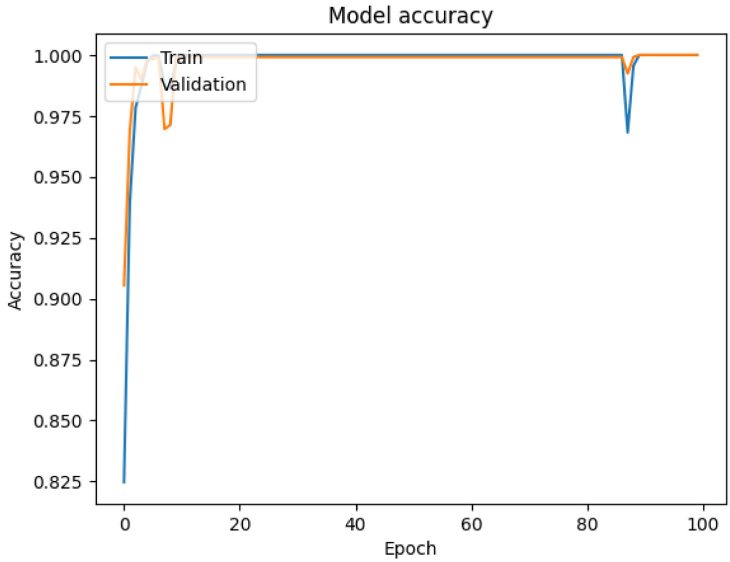

Figure 10

VGG 16 Accuracy CNN

Table 2

Accuracy

Model	Training Loss	Validation Loss	Test Accuracy
VGG 16 with Dense Layer	1.0585e-05	0.0417	0.9941
VGG 16 with 2D CNN	1.0585e-05	0.0417	0.9941
EfficientNetB0 with Dense Layer	1.0585e-05	0.0417	0.9941
EfficientNetB0 with 2D-CNN	0.1023	0.0654	0.9863
ResNet-50 with Dense Layer	0.6619	0.7438	0.6709
ResNet-50 With 2D-CNN	0.4040	0.5829	0.7857
GoogleNet with Dense Layer	0.0818	0.1018	0.9865
GoogleNet with 2D-CNN	0.0954	0.0673	0.9857

Table 3

F1-Score results

Model	Bacterial Blight	Blast	Brown Spot	Tungro
EfficientNetB0 with Dense	0.2758	0.2405	0.2715	0.1822
VGG with 2D CNN	0.2694	0.2715	0.2683	0.2519
VGG with Dense Layer	0.3043	0.2509	0.2715	0.1899
GoogleNet with 2D CNN	0.2665	0.2457	0.2571	0.2180
GoogleNet with Dense Layer	0.2729	0.2710	0.2741	0.2069
ResNet-50 with Dense Layer	0.3498	0.0608	0.2786	0.2505
ResNet-50 with 2D-CNN	0.3457	0.0654	0.2810	0.2488

Table 4

Recall results

Model	Bacterial Blight	Blast	Brown Spot	Tungro
EfficientNetB0 with Dense	0.2753	0.2431	0.2719	0.1801
VGG with 2D CNN	0.2690	0.2743	0.2688	0.2490
VGG with Dense Layer	0.3038	0.2535	0.2719	0.1877
GoogleNet with 2D CNN	0.2627	0.2500	0.2563	0.2184
GoogleNet with Dense Layer	0.2690	0.2743	0.2750	0.2069
ResNet-50 with Dense Layer	0.4367	0.0347	0.3156	0.2529
ResNet-50 with 2D-CNN	0.4310	0.0401	0.3188	0.2507

Table 5

Precision

Model	Bacterial Blight	Blast	Brown Spot	Tungro
EfficientNetB0 with Dense	0.2762	0.2381	0.2710	0.1843
VGG with 2D CNN	0.2698	0.2687	0.2679	0.2549
VGG with Dense Layer	0.3048	0.2483	0.2710	0.1922
GoogleNet with 2D CNN	0.2704	0.2416	0.2579	0.2176
GoogleNet with Dense Layer	0.2769	0.2678	0.2733	0.2069

Contd...

ResNet-50 with Dense Layer	0.2918	0.2439	0.2494	0.2481
ResNet-50 with 2D-CNN	0.2899	0.2510	0.2512	0.2479

Table 6
Specificity

Model	Bacterial Blight	Blast	Brown Spot	Tungro
EfficientNetB0 with Dense	0.7376	0.7503	0.7295	0.7749
VGG with 2D CNN	0.7353	0.7603	0.7283	0.7944
VGG with Dense Layer	0.7480	0.7536	0.7295	0.7771
GoogleNet with 2D CNN	0.7422	0.7480	0.7272	0.7781
GoogleNet with Dense Layer	0.7445	0.7592	0.7295	0.7760
ResNet-50 with Dense Layer	0.6145	0.9654	0.6486	0.7835
ResNet-50 with 2D-CNN	0.6210	0.9709	0.6501	0.7804

V. Conclusion and future scope

This study demonstrates the effectiveness of deep learning for rice disease detection using plant leaf images. A VGG-based model was developed to identify four rice diseases, outperforming traditional machine learning approaches in both accuracy and speed. The architecture of VGG, with its simple design of 3×3 filters and max pooling layers, proved highly effective and easy to implement. Data augmentation techniques such as rotation, scaling, and color adjustments were applied to improve classification performance. In comparison, InceptionV3, with its inception modules, batch normalization, and auxiliary classifiers, also showed strong results, while EfficientNetB0 introduced compound scaling for optimized efficiency. Among these, VGG and InceptionV3 with Dense Layers emerged as top-performing models [9] for rice disease classification. The findings highlight the potential of deep learning to provide smart agriculture solutions, enabling farmers to detect and manage diseases early, thereby improving yield and crop quality. Future research can extend this work by exploring advanced CNN architectures like EfficientNetB0 and ResNet50, which may further enhance productivity, reduce losses, and strengthen sustainable agriculture outcomes.

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