AN EFFICIENT DEEP LEARNING APPROACH FOR RICE DISEASE DETECTION USING A PRE-TRAINED INCEPTIONV3 NETWORK

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Abstract

Rice is one of the world's most important staple crops, and its production is significantly affected by various diseases that reduce both yield and quality. Rice diseases can cause yield losses of up to 40%, resulting in substantial economic consequences for the agricultural sector and the global economy. Therefore, timely and accurate disease diagnosis is essential for effective crop management and minimizing financial losses. Although recent technological advancements have improved agricultural practices, rice disease identification still largely depends on manual inspection by experts. This study proposes a novel InceptionV3-based deep learning model for accurate AI-assisted rice disease classification using transfer learning. The proposed model employs a pre-trained network to extract discriminative features and capture contextual information from rice leaf images, thereby improving classification performance. To evaluate the proposed approach, classification experiments were conducted on a publicly available rice disease dataset containing four classes. Experimental results demonstrate that the proposed model effectively learns disease-specific features, resulting in high classification accuracy and reduced prediction variance. The proposed InceptionV3 model achieved a test accuracy of 98.8%, outperforming several state-of-the-art deep learning models. These findings demonstrate the potential of artificial intelligence and deep learning for automated rice disease detection, contributing to improved agricultural productivity, sustainable crop management, and enhanced decision-making.

Keywords : Rice disease classification, InceptionV3, Transfer learning, Deep learning, Artificial intelligence, Image classification, Precision agriculture.

I. INTRODUCTION

Rice is one of the world's most important staple crops, serving as the primary food source for a large proportion of the global population. However, rice production is significantly affected by various diseases that reduce crop growth, quality, and yield. According to the Food and Agriculture Organization (FAO), plant pests and diseases cause annual agricultural losses exceeding USD 220 billion worldwide [1]. Therefore, early identification and accurate diagnosis of rice diseases are essential for minimizing yield losses, improving crop productivity, and reducing economic damage.

In many agricultural regions, rice disease diagnosis still relies on manual inspection by experienced farmers or agricultural experts. This traditional approach is labor-intensive, time-consuming, and susceptible to human error, particularly when symptoms appear similar during the early stages of infection. The widespread availability of smartphones and digital imaging devices has enabled farmers to capture high-quality images of infected crops, creating opportunities for automated disease diagnosis using computer vision and artificial intelligence (AI) techniques. Recent advances in image processing and computer vision have significantly improved the accuracy and efficiency of plant disease detection systems [2].

Pesticides remain the primary method for controlling plant diseases in modern agriculture. However, excessive or inappropriate pesticide application can lead to environmental degradation, increased production costs, and adverse effects on human health. Consequently, accurate disease diagnosis is crucial for recommending appropriate treatment strategies while minimizing unnecessary pesticide usage [3].

Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have achieved remarkable success in image classification and plant disease recognition tasks due to their ability to automatically extract discriminative features from images. Numerous studies have demonstrated the superior generalization capability of CNN-based models in agricultural applications [4]. For instance, residual neural networks have been successfully employed for disease detection in tomato leaves [5], while several deep learning classifiers have achieved promising performance in rice disease recognition [6]. Moreover, attention mechanisms have further enhanced model performance by enabling neural networks to focus on disease-relevant regions and capture contextual dependencies within images [7]. Previous studies

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have also shown that appropriate activation and loss functions significantly influence the learning capability and classification accuracy of deep neural networks [8]. Despite these advancements, there remains a need for highly accurate and computationally efficient models specifically designed for rice disease classification.

To address these challenges, this study proposes a transfer learning framework based on the InceptionV3 architecture for automated rice disease classification. The proposed model incorporates a multi-scale feature extraction mechanism that effectively captures both local and global contextual information from rice leaf images. Furthermore, transfer learning enables the model to leverage pre-trained ImageNet weights, thereby reducing training time, computational complexity, and the amount of labeled training data required.

Unlike conventional CNN-based approaches, the proposed framework utilizes a kernel attention mechanism to improve feature representation by emphasizing disease-specific regions and capturing long-range dependencies within feature maps [9]. Kernel attention has recently demonstrated excellent performance in remote sensing image segmentation by enhancing contextual feature aggregation [10]. Inspired by this concept, the present study adapts kernel attention for rice disease classification, enabling the network to learn more informative and discriminative features from rice leaf images. In addition, feature visualization techniques are employed to improve the interpretability of the proposed model by illustrating how the network extracts disease-related characteristics from different convolutional layers.

The major contributions of this study are summarized as follows:

- Development of an InceptionV3-based deep learning framework for accurate and automated rice disease classification.
- Integration of a kernel attention mechanism to enhance multi-scale feature extraction and capture long-range contextual dependencies.
- Application of transfer learning to reduce computational complexity, accelerate model convergence, and improve classification performance.
- Comprehensive experimental evaluation demonstrating the superiority of the proposed approach over several state-of-the-art deep learning models.

The remainder of this paper is organized as follows. Section 2 reviews recent studies related to rice disease detection and deep learning techniques. Section 3 describes the proposed methodology and network architecture. Section 4 presents the experimental results and performance analysis. Finally, Section 5 concludes the paper and discusses future research directions.

II. RELATED WORKS

Recent advancements in deep learning have significantly improved the automated diagnosis of rice diseases. Convolutional Neural Networks (CNNs) have demonstrated remarkable performance in extracting discriminative features from plant leaf images, enabling accurate disease classification. In particular, the study presented in [11] proposed a CNN-based framework for rice disease detection using images of both healthy and diseased rice leaves. The dataset consisted of ten different rice disease classes collected from agricultural fields. The proposed model achieved a classification accuracy of 95.48% using a 10-fold cross-validation strategy, demonstrating the effectiveness of CNNs for rice disease diagnosis.

The study in [12] employed two state-of-the-art deep learning architectures, InceptionV3 and VGG16, for rice disease classification. The proposed transfer learning approach successfully classified multiple rice diseases and demonstrated the practical applicability of pre-trained convolutional neural networks for real-world agricultural datasets. Experimental results confirmed that both architectures provided high classification performance while reducing the need for extensive feature engineering.

To develop lightweight models suitable for resource-constrained environments, the study in [13] proposed a two-stage compact CNN architecture and compared its performance with memory-efficient networks such as SqueezeNet, NASNet-Mobile, and MobileNet. The proposed lightweight architecture achieved an accuracy of 94% while significantly reducing the model size and computational complexity, making it suitable for deployment on mobile and embedded devices.

The study in [14] developed a comprehensive rice leaf disease dataset and proposed a CNN-based feature extraction and classification framework. The extracted deep features were further classified using a Support Vector Machine (SVM) classifier. Experimental results demonstrated that the hybrid CNN–SVM approach outperformed conventional feature extraction methods, including Haar Wavelet Transform (Haar-WT) and Local Binary Pattern (LBP) descriptors, in terms of classification accuracy and the Area Under the Curve (AUC). These findings highlighted the superior discriminative capability of deep learning-based feature representations over traditional handcrafted features.

To improve disease detection accuracy, the study in [15]

integrated image processing techniques with an optimized deep neural network using the Jaya optimization algorithm. The proposed framework classified healthy rice leaves and several disease categories, including sheath rot, blast, bacterial blight, and brown spot diseases. During preprocessing, RGB images were converted to the HSV color space to eliminate background noise. Color and saturation components were subsequently used to segment healthy and infected leaf regions before feature extraction. The optimized deep neural network achieved classification accuracies of 99.9%, 96%, 93%, 95%, and 91% for sheath rot, brown spot, bacterial blight, blast, and healthy leaves, respectively.

Apart from image-based diagnosis, Internet of Things (IoT)-based disease monitoring systems have also been investigated. An IoT-enabled platform, RiceTalk, was developed to detect rice blast disease using environmental sensor data instead of image analysis. Based on soil and environmental measurements, the system achieved an accuracy of 90% in rice blast disease prediction, demonstrating the potential of IoT technologies for precision agriculture.

Although previous studies have reported promising classification performance, several limitations remain, including high computational complexity, limited feature representation, and insufficient utilization of contextual information. These challenges motivate the development of more robust and computationally efficient deep learning frameworks. Consequently, this study proposes an InceptionV3-based transfer learning model enhanced with a kernel attention mechanism to improve feature extraction, capture long-range contextual dependencies, and achieve superior rice disease classification performance.

III. METHODOLOGY

A. Dataset

This study focuses on the classification of three common rice diseases: rice hispa, brown spot, and rice leaf blast, along with healthy rice leaves. Traditionally, rice disease diagnosis is performed through visual inspection of disease symptoms by agricultural experts.

Brown spot is characterized by dark brown, circular or oval lesions surrounded by a yellow halo. The lesions vary in size and typically exhibit a reddish-brown to dark brown border with a gray necrotic center.

Rice hispa damages the epidermal layer of rice leaves by feeding on the leaf tissue, resulting in reduced plant vigor and poor crop health. The severity of infestation can be visually assessed by examining the extent of leaf damage caused by the insect.

Rice leaf blast is characterized by small black spots or elongated diamond-shaped lesions with gray or white centers surrounded by reddish-brown margins. As the disease progresses, the lesions enlarge and merge, causing severe damage to the leaf tissue and reducing photosynthetic activity.

The dataset used in this study consisted of 2,370 rice leaf images, including healthy leaves and leaves infected with rice hispa, brown spot, and rice leaf blast. These images were used to train and evaluate the proposed deep learning model for automated rice disease classification.

B. Prediction

The proposed classification framework employs the InceptionV3 architecture, an improved version of the InceptionV1 network, for automated rice disease classification. InceptionV3 enhances feature extraction capability through a deeper architecture and optimized convolutional modules, making it highly effective for complex image classification tasks.

Training deep convolutional neural networks from scratch requires a large amount of labeled data and considerable computational resources. To overcome these challenges, transfer learning is adopted by utilizing pre-trained ImageNet weights. In the proposed approach, the feature extraction layers of the InceptionV3 model are retained, while the final classification layer is replaced with a new fully connected layer corresponding to the four rice disease classes. During training, the pre-trained convolutional layers remain frozen, and only the newly added classification layers are fine-tuned using the rice disease dataset.

As illustrated in Fig. 1, the proposed InceptionV3 architecture consists of 48 layers with newly added classification layers tailored to the target dataset. Compared with conventional deep learning architectures such as VGG16, VGG19, and AlexNet, which employ sequential convolutional and pooling layers, InceptionV3 utilizes 1×1 pointwise convolutions followed by convolutional filters of different kernel sizes within the same module. This multi-scale architecture enables efficient feature extraction while reducing computational complexity.

The multi-scale convolutional design allows the network to capture both local and global image features simultaneously, resulting in improved representation of disease characteristics. Consequently, the proposed InceptionV3-based transfer learning model achieves superior feature extraction and classification performance, making it well suited for complex rice disease recognition tasks.

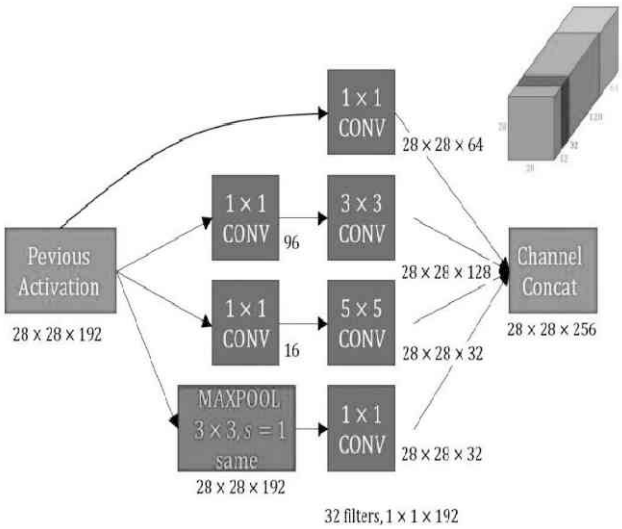

Fig 1: Inception V3 with CNN architecture

IV. NUMERICAL RESULTS

The F1-score and classification accuracy were determined using the cumulative confusion matrix to assess Inception V3's performance on the rice illness classification dataset. In machine learning, models are evaluated using an F1 score, which gauges their performance. In essence, it averages the recall and precision of a model.

$$Classification_accuracy = \frac{\sum_{k=1}^{N} TP}{\sum_{k=1}^{N} TP + FP + TN + FN} \quad (1)$$

$$F1 = 2 * \frac{precision * recall}{precision + recall} \quad (2)$$

Here, $TP_k, FP_k, TN_k, and\ FN_k$ represent true positives, false positives, and false negatives, respectively. For every class, the classification accuracy was computed. A dataset of 400 photos with four disease types identified on them was used in our tests. As indicated in Table 1, the suggested model was contrasted with several existing deep learning models, including MobileNetV1, ViT, Xception, ResNet50, InceptionV3, Dense-Net121 and VGG16. ImageNet assessed each CNN model with pre-trained weights using the same architecture as the original CNN model and five-fold CV. The evaluated findings are shown in Table 1 according to the performance indicators covered in the assessment standards. The table displays each measurement's mean and SD. The 5-fold CV findings validated these values. The bolded characters indicate the deep learning models with the highest evaluation scores.

Table 1: Comparative analysis

Model	Precision	Recall	FI-score	Accuracy
ResNet	88	81	84	90
DenseNet	62	76	64	79
MobileNet	85	90	86	91
VGG16	22	63	35	67
ViT	70	65	65	83
Efficient	84	76	78	88
Inception v3+CNN	**99**	**98**	**98.9**	**98.8**

The recommended Inception V3 model obtained the highest possible F1 score, recall, accuracy, and precision with the least performance variability. Table 1 shows that the Inception V3 outperformed the ViT by 1.6% in precision, 1.5% in F1-score and 1.6% in accuracy with the same 28.5 million parameters. Additionally, the proportional benefits of the accurate models were contrasted with the overall performance of Inception V3. The F1-score and accuracy of the model are displayed in box plots in Fig 2. In terms of correctly categorizing images with a lower error rate for all varieties of rice sickness, the Inception V3 fared better than previous models. Our examination of numerous disease categories indicates that leaf blast disease is challenging rice illness to classify. Comparing the leaf blast illness to other diseases covered in this investigation, like harm from rice hispa and brown spots, it is the most challenging to categorize.

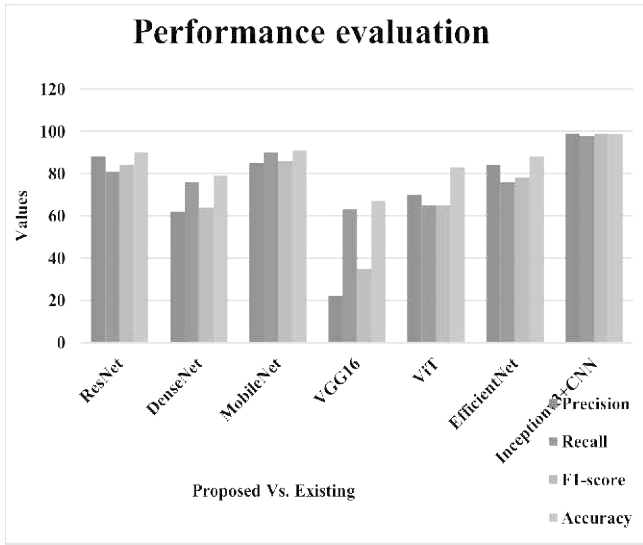

Fig 2: Performance evaluation

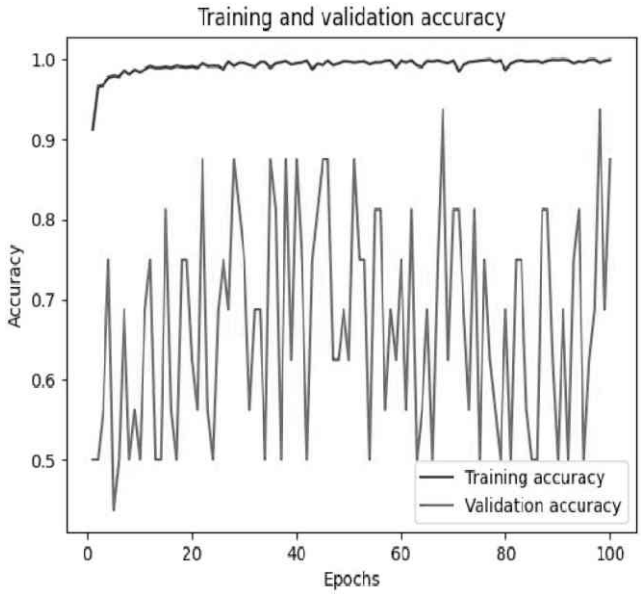

Fig 3: Accuracy analysis

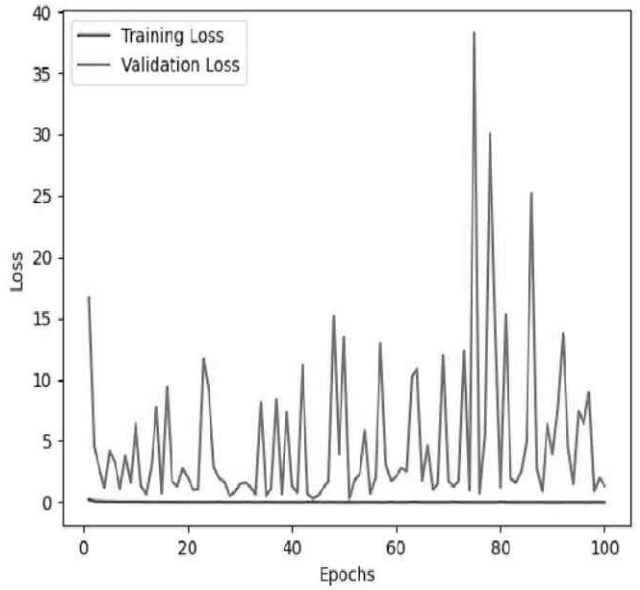

Fig 4: Loss analysis

This is a result of the arrangement in each lesson. Brown spots are dark brown, flat lesions with halo surrounding them as described. They are frequently spherical or oval. There is no geographical restriction on brown spots; any part of the plant's body may have them. If the hispa is discovered on the rice leaf, it is relatively simple to assess the degree of damage it has caused. However, lesions brought on by rice leaf blasts can vary from little black dots to larger patches with the gray or white core and a reddish ring. The disease gradually deteriorates the leaf tissue, resulting in the demise of the outer layer of the leaf blades' epidermis.

V. CONCLUSION

This study presents an effective deep learning framework for automated rice leaf disease classification using the InceptionV3 architecture with transfer learning. The proposed model integrates a kernel attention mechanism into the network to enhance contextual feature extraction across different encoder levels, enabling the learning of more discriminative semantic representations from rice leaf images. Consequently, the model effectively captures both local and global disease characteristics, resulting in improved classification performance.

Extensive experiments conducted on the rice disease dataset demonstrate that the proposed InceptionV3 model outperforms several state-of-the-art deep learning models in terms of accuracy, precision, recall, and F1-score. In addition, activation map visualization, filter analysis, and feature evaluation confirm the effectiveness of the proposed architecture in accurately identifying disease-specific regions. The experimental results indicate that the proposed model achieves superior classification performance with minimal performance variation, making it a reliable and efficient solution for automated rice disease diagnosis.

Overall, the proposed framework has significant potential for real-world applications in precision agriculture by assisting farmers and agricultural experts in the early detection of rice diseases, thereby improving crop management, reducing yield losses, and supporting sustainable agricultural practices. Future work will focus on evaluating the proposed model on larger and more diverse datasets, optimizing its computational efficiency, and deploying it in real-time mobile and IoT-based agricultural monitoring systems.

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