A Diseased Rice Plant Detection Method Based on Transfer Learning Technique

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Abstract. Early detection of diseases in rice plants is crucial for ensuring crop health and optimizing yield. Traditional methods of disease identification are time-consuming and require expert knowledge, which limits their practical application in large-scale agriculture; using drones equipped with cameras and computer vision systems will be an effective solution. This paper presents a rice plant disease detection method using transfer learning techniques on images captured from the view of drones. We leverage EfficientNet B0 pre-trained to extract features from images of rice field regions and fine-tune these networks to distinguish diseased rice from disease-free rice. Our dataset comprises high-resolution images of healthy rice fields and regions affected by common diseases such as bacterial blight, brown spots, and leaf blasts. Experimental results demonstrate that the proposed method outperforms popular image classification methods based on CNN for Rice Plant Disease Detection in our dataset in terms of accuracy and inference time.

Keywords: Rice Plant Disease Detection, Transfer Learning, Deep Learning.

1 Introduction

Rice is one of the most important staple crops worldwide, especially in Vietnam, serving as the primary food source for more than half the global population [8]. Ensuring the health and productivity of rice crops is paramount for food security. However, rice plants are susceptible to various diseases like brown spot, bacterial blight, blast, sheath blight, false smut, bakanae, and sheath, which can significantly reduce yield and quality [4]. Timely and accurate detection of these diseases is essential for effective disease management and the application of appropriate treatment measures.

Traditional methods for identifying rice plant diseases involve visual inspection by agricultural experts, which is labor-intensive, time-consuming, and often impractical for large-scale farming operations. Additionally, these methods can be subjective and prone to human error [9]. The advancement of machine learning and image processing techniques offers promising alternatives for automating the disease detection process. In particular, convolutional neural networks (CNNs) have demonstrated exceptional performance in image classification tasks [7], making them suitable for identifying plant diseases from images.

Despite CNNs' success, training deep learning models from scratch requires large amounts of labeled data and significant computational resources. To address these challenges, transfer learning has emerged as a powerful technique [22]. Transfer learning involves leveraging pre-trained models, which have been previously trained on large datasets, and fine-tuning them on specific tasks with relatively smaller datasets. This approach reduces the need for extensive data collection, accelerates the training process, and improves the performance of the model.

Regarding the problem of detecting diseased rice plants, many studies have used traditional machine learning methods and deep learning [14, 17]. However, these studies were all performed on close-up images of rice leaves, not images of rice field regions captured from a drone's view.

In this paper, we propose a rice plant disease detection method based on a transfer learning technique that works on images of rice field regions captured from a drone's view. Our study involves collecting a dataset and fine-tuning the EfficientNet B0 architecture [19]. We thoroughly evaluate the accuracy of the proposed model and compare it with other options. The contributions of this paper are threefold:

1. We proposed using pre-trained EfficientNet B0 to fine-tune a model for detecting diseased rice plants in images captured from drones' views.
2. We provide a dataset comprising high-resolution images of healthy rice fields and regions affected by common diseases captured from drone view.
3. We provide detailed experiments and compare the proposed model performance with other options.

The remainder of this paper is organized as follows: Section 2 reviews related works. Section 3 describes the proposed method. Section 4 presents the experiments. Finally, Section 5 concludes the paper.

2 Related works

In high-tech agriculture, machine learning and image processing have seen significant advancements in recent years [14]. Specifically, the detection of plant diseases using image-based techniques has gained considerable attention due to the potential for automation and scalability. This section reviews the existing literature on plant disease detection, focusing on machine learning, deep learning, and transfer learning methods for rice plant disease detection.

A range of traditional machine learning algorithms have been applied to the detection of rice plant diseases, with promising results [12]. [1] achieved over 97% accuracy using decision tree, while [6] found that the random forest classifier provided the highest accuracy. [5] proposed a methodology using image processing and machine learning, achieving accuracies of 89.19% for leaf blight, 82.86% for brown spot, and 89.19% for leaf blast. [20] provided a comprehensive overview of machine learning methods for disease detection in rice plants, emphasizing the importance of selecting appropriate classification methods.

Various deep-learning methods have been proposed for detecting rice plant diseases, each demonstrating high levels of accuracy [17]. Babu et al. [3] and Chen et al. (2020) reported notable results, with Babu's method achieving an accuracy of 99.45% and Chen's method reaching 98.63%. In 2023, Venkatesh et al. [21] and Felicia et al. [2] also employed deep learning techniques, with Venkatesh achieving 99.8% accuracy using Convolutional Neural Networks (CNNs) and Felicia introducing a DL-ARPDRC technique that surpassed other contemporary methods.

In addition, a range of studies have explored the use of transfer learning for rice plant disease detection, yielding promising results. Kanuparthi et al. [13] and Mohapatra et al. [15] achieved high accuracy in detecting common rice diseases using ensembled transfer learning models and a transfer learning-based AlexNet model, respectively. Singh et al. [18] and Gogoi et al. [10] also demonstrated the effectiveness of transfer learning, with Singh using a MobileNet model to identify three significant rice plant diseases and Gogoi implementing a 3-stage CNN architecture with transfer learning for high accuracy in disease detection. These studies collectively highlight the potential of transfer learning in enhancing rice plant disease detection accuracy and efficiency.

In summary, traditional machine learning methods initiated automated plant disease detection, but deep learning approaches, particularly CNNs, excelled due to superior feature extraction. Transfer learning further enhances deep learning by leveraging pre-trained models, reducing data needs, and boosting performance. However, prior studies focused on close-up rice leaf images, unlike our approach using drone-captured images of entire rice field regions.

3 Rice Plant Disease Detection Using Transfer Learning Technique

This section presents the detailed architecture of our proposed model for rice plant disease detection using transfer learning with EfficientNet B0. Figure 1 illustrates our transfer learning pipeline. We usually need to follow several key steps to design a deep learning model for a specific classification problem based on transfer learning techniques: choose the backbone, select pre-trained weights, decide on a fine-tuning strategy, design custom fully connected layers, and define the output layer. These steps ensure the model is tailored to the task's specific requirements while leveraging the strengths of pre-existing architectures and learned features. Next, we will detail the implementation of these steps in our proposed method.

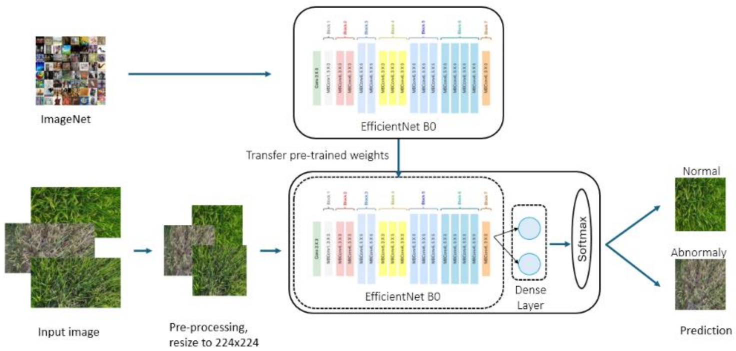

Fig. 1. Proposed transfer learning pipeline.

Backbone selection: The backbone of our model is EfficientNet B0[19], a state-of-the-art convolutional neural network architecture renowned for its exceptional efficiency and performance. EfficientNet B0, as part of the EfficientNet family, employs a compound scaling method to balance network depth, width, and resolution in a structured manner. This unique approach enables EfficientNet models to achieve high accuracy while maintaining a compact size and lower computational cost than other deep learning architectures. Empirical research further justifies our choice of EfficientNet B0, as detailed in Section Experiments (Sub-section 4.2).

Using Pre-trained ImageNet Weights: We selected pre-trained weights from the ImageNet dataset for our model to leverage the extensive visual features the model has already learned from millions of images across thousands of categories. Using these pre-trained weights allows our model to start with a robust foundation, significantly enhancing its ability to generalize from limited domain-specific training data. This transfer learning strategy not only improves performance but also makes the training process more efficient and practical for real-world applications.

Fine-tuning Strategy: We chose to re-train all feature extraction layers of EfficientNet B0 instead of freezing them. This allows the model to adapt pre-trained features to the specific characteristics of rice plant disease images. By fine-tuning the entire network, both low-level features (edges, textures) and high-level patterns are optimized for our dataset. Although more computationally intensive, this approach improves performance and accuracy.

Design of Fully Connected Layers for Classification: For the classifier, we opted for a simple architecture consisting of one hidden layer with 2 nodes, followed by a softmax layer for classification. This minimalist design was chosen to avoid overfitting and to ensure that the model remains efficient and easy to train.

4 Experiments

4.1 Dataset and Experimental Environment

Fig. 2. Each input image is a 1920x1080 pixel RGB image, categorized into two classes: Normal (Left) and Anomaly (Right).

Our dataset[1] comprises a total of 7,362 images, each simulating a drone's top-down view of a rice field. Figure 2 illustrates two random samples from each class in the dataset. There are 5,672 images in the Normal class and 1,690 in the Anomaly class, we divided these images into three sets: training, validation, and testing, with a ratio of 7:1:2. The detailed data splitting is presented in Table 1.

Table 1. Data splitting

	Normal	**Anomaly**	**Total**
Train	3,970	1,183	5,153
Validation	568	170	738
Test	1,134	337	1,471

In our study's experimental setup, we trained models on a high-performance computing (HPC) system with an Intel Xeon Gold 6226R CPU 32 cores, 64GB of RAM, and an RTX A5000 GPU. The testing phase used 8 cores on the same CPU.

Regarding the hyperparameter configuration for training each model, we retained their original settings from [11], [18], and [19] for ResNet50, MobileNet, and Effi-

[1] https://github.com/dtungpka/RicePlantDiseaseDetection

cientNet B0, respectively. However, we experimented with different learning rates, as detailed in Sub-section 4.4, to determine the optimal value for our models.

4.2 Comparasion with other backbones

We conducted experiments on EfficientNet B0 and two other models, ResNet50 and MobileNet. These models were evaluated under the best settings and compared in two aspects: accuracy and inference time. The results are shown in Table 2. These models have been reported to perform well on edge devices [16]. Specifically, EfficientNet has a mean inference time of 19.64ms on a Jetson FP16 device, ResNet50 has a mean inference time of 35.13ms, and MobileNet has a mean inference time of 12.08ms [16]. In our study, using 8 cores on an Intel Xeon Gold 6226R (32 cores) CPU yields a similar result. ResNet50 and EfficientNet B0 achieve the same high accuracy. However, the execution time of EfficientNet B0 used in our solution is almost twice as fast.

Table 2. Comparasion with other backbones

Backbone	**Accuracy**	**Inference time (ms)**
ResNet50	**1.0000**	48
MobileNet	0.9937	**18**
EfficientNet B0 used in our solution	**1.0000**	29

4.3 Performance Analysis of Pre-Trained Models and Fine-Tuning Strategies

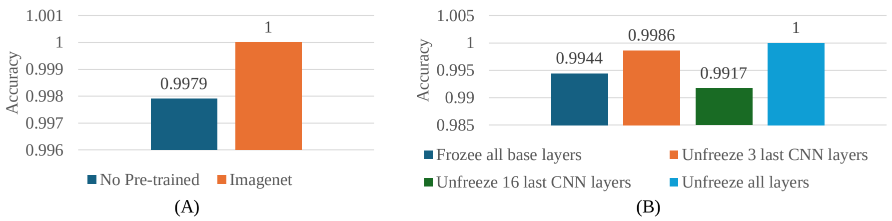

Fig. 3. Analysis of Pre-Trained Models (A) and Fine-Tuning Strategies (B)

In our experiments, we evaluated the performance of our model with and without pre-training on the ImageNet dataset. As shown in Fig.3(A), the results indicate that pre-training on ImageNet enhances the model’s accuracy. Specifically, Efficient-

NetB0 achieves perfect accuracy when pre-trained, highlighting the effectiveness of transfer learning.

Furthermore, we explored the necessity of re-training all layers versus retraining some high-level layers and freezing all layers. The results of this experiment are shown in Fig.3(B). We can see that re-training all layers leads to optimal performance, as evidenced by the perfect accuracy of EfficientNetB0. This result suggests that allowing the model to adjust all parameters, even those pre-trained on ImageNet, is crucial for adapting to the specific task of rice plant disease detection.

4.4 Investigation of Hyperparameters

We investigated the influence of the learning rate value on the model. As shown in Fig.4, a learning rate of 0.1, the model's accuracy noticeably decreases, especially when the model is not pre-trained. The main reason for this phenomenon is that the training process is difficult to converge with a large learning rate. In contrast, a lower learning rate of 0.01 and 0.001 results in much higher accuracy, with the pre-trained EfficientNet B0 model achieving perfect accuracy. When the learning rate is too low, for example, 0.0001, the training process still converges, but the convergence speed is plodding. Selecting the correct learning rate is crucial as it influences the convergence speed and the overall effectiveness of the model.

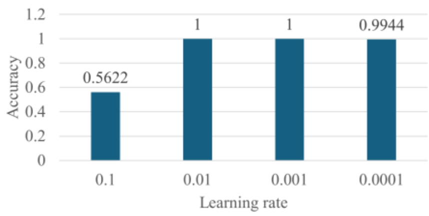

Fig. 4. Comparison between different learning rates

5 Conclusions

In this study, we introduced a rice plant disease detection method using transfer learning with EfficientNet B0. Our model demonstrated high accuracy, showcasing its potential. Future work will focus on collecting more diverse datasets to improve robustness and applicability, and conducting further experiments to enhance performance in varied conditions.

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