Paddy Disease Classification Based on the Lightweight MobileNet-V2

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Abstract. Paddy, a critical global staple food and economic resource, faces significant challenges in cultivation due to diseases that have devastating effects on crop yield and quality. Accurate and valid classification of these diseases is essential for their effective prevention, management, and timely treatment. Traditional identification methods, which are manual, time-consuming, labor-intensive, and prone to misclassification, fail to efficiently address these concerns. In response to these limitations, this research focuses on designing a lightweight neural network model for rice disease classification, leveraging the power of MobileNet-V2. This deep separable convolution-based neural network architecture is optimized for efficiency and accuracy in image classification tasks, making it well-suited for mobile devices. The approach enables real-time identification of rice diseases in the field, facilitating prompt intervention and treatment, ultimately minimizing the impact on crop yield and quality. The proposed model has undergone rigorous testing and benchmarking against state-of-the-art methods in paddy disease classification. Sufficient and multifaceted results demonstrate that the designed method achieves superior performance, outperforming the state-of-the-art in terms of accuracy and efficiency. The utilization of MobileNet-V2 in this research offers a valuable solution for the rapid and precise diagnosis of rice diseases, significantly contributing to the minimization of their spread and impact on crop yield and quality.

Keywords: Paddy Disease classifier; MobileNet-V2; Lightweight.

1. Introduction

Paddy [1], commonly referred to as rice, serves as a critical food staple for many cultures while also playing a pivotal role in the economy and livelihoods of millions worldwide. Notwithstanding, Paddy cultivation confronts several hurdles, with one of the significant issues being diseases that attack the crops. These diseases can cause devastating effects, resulting in significant losses of yield and quality. Therefore, efficient and accurate classification of these diseases is essential in preventing and managing the spread of the diseases.

Paddy diseases are instigated by various factors, including fungi, bacteria, viruses, and nematodes [2-4]. These diseases are challenging to diagnose visually, as they manifest with similar symptoms, such as yellowing, wilting, and stunting, making it difficult to differentiate and identify them correctly. Accurate diagnosis is critical as it leads to timely and targeted treatment and reduces losses resulting from crop diseases. The traditional identification of paddy diseases is carried out manually, mainly by experienced farmers or agronomists using manual methods to analyze and identify samples one by one. This approach is not only time-consuming and labor-intensive, but it is also prone to misclassification.

In order to realize the intelligent identification of Paddy disease classification, numerous solutions have been proposed by researchers worldwide. In this regard, machine learning techniques have been explored to develop efficient and accurate classification models to diagnose paddy diseases. Several machine-learning techniques have been explored in the classification of paddy diseases [5-7]. These methods include decision trees [8], K-nearest neighbors [9], support vector machines [10], and artificial neural networks as well as Convolutional Neural Networks (CNNs). Decision trees are easy to interpret and understand. They can be visualized and help to understand the reasons behind decisions. In the process of Paddy's classification of diseases, categorical data, and numerical data can be processed, and missing values and outliers can be processed. But decision trees can easily overfit the data, which can lead to poor performance on new data. K-nearest neighbor is easy to understand and does not make any assumptions about data distribution in the process of realizing Paddy pest identification. However, K-nearest Neighbor (KNN) is very sensitive to the choice of k, and there is a problem of high computational cost, and KNN needs a large number of samples to accurately classify. Support Vector Machine (SVM) can handle a large number of features, but SVM is computationally expensive and requires a careful selection of kernel functions and regularization parameters. Among these methods, CNNs have shown remarkable performance in image classification tasks due to their ability to learn complex features from images automatically. However, these models have a high computational cost, making them less ideal for mobile devices, which are often used in the field for crop monitoring.

One area of research that has recently received attention is the use of neural networks in the classification of paddy diseases. Neural networks are computational models that mimic the structure and function of the human brain, comprising multiple interconnected processing nodes called neurons. The networks are trained using large amounts of data to learn the underlying patterns and features of the input data, enabling them to make accurate predictions.

Aiming at the problems of low classification accuracy and high computational cost in the field of Paddy disease classification, this research is dedicated to designing a lightweight neural network model for Paddy disease classification. MobileNet-V2 is a neural network architecture optimized for efficient and accurate image classification tasks on mobile devices [11]. The architecture is based on depthwise separable convolutions, which are computationally efficient and reduce the model size, making them ideal for use in mobile devices. Therefore, this study migrated MobileNet-V2 for application in rice disease classification.

Specifically, the main work and contributions of this paper are as follows:

(1) Migrate MobileNet-V2 to the task of Paddy disease classification. The model has been trained and tested on a dataset containing images of various paddy diseases and achieved a level of high accuracy, outperforming other traditional machine learning models.

(2) Furthermore, the size and computational cost of the model make it ideally suited for deployment on mobile devices, enabling real-time diagnosis of rice diseases in the field.

(3) This study proposes a mobile-optimized neural network architecture that provides a solution for the accurate classification of Paddy diseases to prevent and manage the spread of these diseases, thereby increasing yield and improving crop quality.

The remainder of each chapter is as follows. First, in the second chapter, this study introduced the method and principle of the design in detail. Section third is mainly about results and discussion. Finally, in the conclusion part, the content of the full text is summarized and prospected.

2. Method

2.1. Dataset description and preprocessing

The dataset used in this study was obtained from the Kaggle competition [12], comprising 13,876 RGB images of paddy leaves belonging to ten different classes: nine types of diseases and one normal leaf. Each image has a unique identifier and a label indicating its class. The dataset also provides some additional information about each image, such as the variety and age of the paddy plant. Some samples of the dataset are shown in Fig. 1. The objective of using this dataset is to train a machine learning model that can accurately classify the images into their respective classes. The dataset is split into two parts: a training set with 10,407 images (75%) and a test set with 3,469 images (25%). The Paddy dataset consists of images of paddy leaves that are affected by different types of diseases or are healthy.

To train a model that can accurately classify these images, some preprocessing steps are required to enhance the quality and diversity of the data. One preprocessing step is to crop the images into smaller patches that contain only the leaf regions and exclude the background. This can help reduce the noise and irrelevant features in the images that may interfere with the model's performance. For example, some images may have soil, water, or other plants in the background that are not related to the leaf condition. By cropping these parts out, the most important features that indicate the disease type can be focused on. Another preprocessing step is to apply some data augmentation techniques to the cropped images. Data augmentation is a process of creating new training samples by applying some transformations to the original images, such as rotation, flipping, scaling, and color jittering. These transformations can introduce some variations and perturbations to the data that can help the model learn more robust and invariant features. Data augmentation can also increase the number of training samples and prevent overfitting. The final preprocessing step is to resize all the images to a fixed size of 224 that matches the input dimension of the model. This can ensure a consistent format for all the images and reduce computational costs during training and inference. Resizing can also preserve some important details in high-resolution images that may be lost if they are down-sampled too much.

Fig. 1 Some samples of the Paddy dataset

2.2. Employed CNN model

The main module of CNN is the convolutional layer, which is responsible for extracting features from the input image. A convolutional layer slides a filter (also called a kernel) over the input image and computes the dot product between the filter and the image region, resulting in a feature map. A pooling layer is a down-sampling operation that divides the feature map into small regions and applies some functions to each region to get a smaller output. The role of the pooling layer is to reduce the number of parameters and increase the robustness and invariance of the model. The fully connected layer is a traditional neural network layer that connects the output of all previous layers to each neuron and uses an activation function for nonlinear transformation. Fully connected layers are usually located at the end of CNNs and are responsible for mapping feature vectors to class labels or other targets.

MobileNet is a lightweight CNN-based model developed by Google in 2017 for efficient computer vision tasks on mobile devices and robots [13]. MobileNet uses techniques such as depthwise separable convolution, linear bottleneck, and inverted residual to reduce the number of parameters and calculations. This study utilizes the TensorFlow framework to implement MobileNet, with the last layer containing 10 neurons to match the task's classification needs. The framework of Paddy's disease recognition algorithm based on MoblieNet-V2 proposed in this study is shown in Fig. 2.

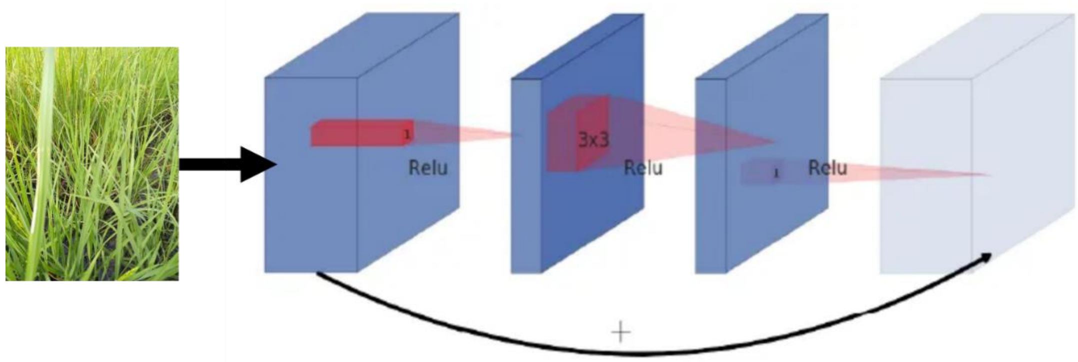

Fig. 2 Paddy's Disease Recognition Framework Based on MoblieNet-V2.

2.3. Implementation details

The training process of the model in this paper involves some hyperparameters and hardware specifications. In this study, a learning rate of 1e-3 was used for the first 30 rounds of training and then reduced to 1e-4 for the last 20 rounds of training. Adam is used as the optimizer and categorical cross-entropy is used as the loss function. The model was trained for 50 epochs, each iteration using 64 samples as the batch size. Accuracy is also used as a metric to evaluate the performance of the model on the validation set. A Tesla T4 GPU was used with 512GB memory and an i7-12700H CPU.

3. Result and discussion

In order to evaluate the effectiveness and efficiency of the proposed paddy disease recognition algorithm based on MobileNet-V2, comparative experiments were conducted with other state-of-the-art models, as well as an analysis of model parameter quantity and paddy disease recognition time.

Firstly, as depicted in Fig. 3, a histogram was constructed to visualize the distribution of each disease category within the dataset, allowing for a more comprehensive analysis of the balance across different categories. Upon observation of Fig. 3, the distribution of various diseases can be intuitively discerned. Fig. 4 and Fig. 5, respectively, illustrate the evolution of training loss, validation loss, training set accuracy, and validation set accuracy. Analysis of these figures indicates that the proposed paddy disease recognition algorithm based on MobileNet-V2 ultimately converges and demonstrates excellent robustness.

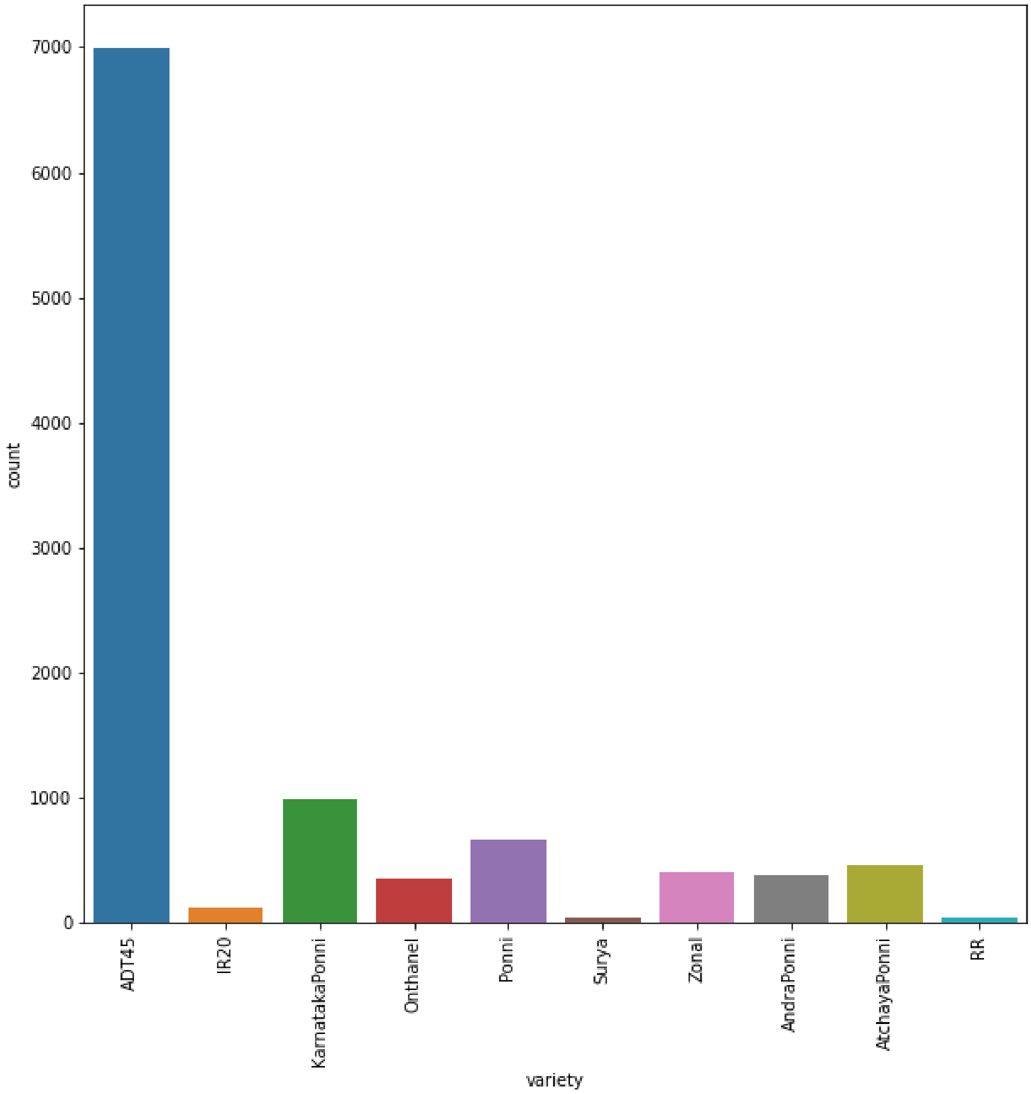

Fig. 3 Distribution plot for each disease category in the dataset

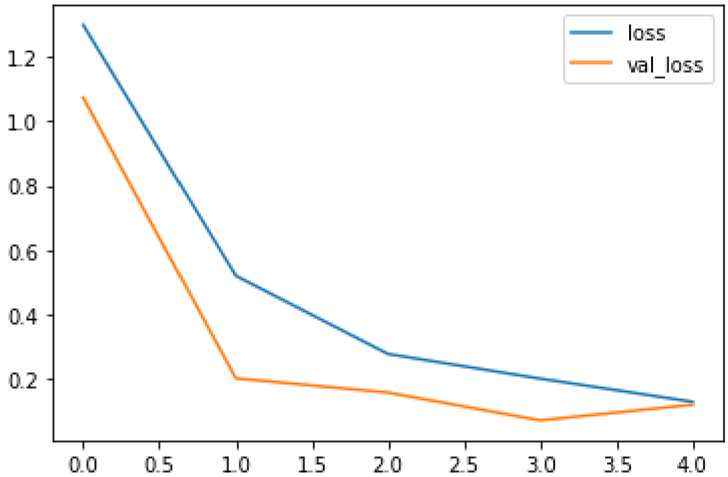

Fig. 4 Training and Validation Loss Variation Curves

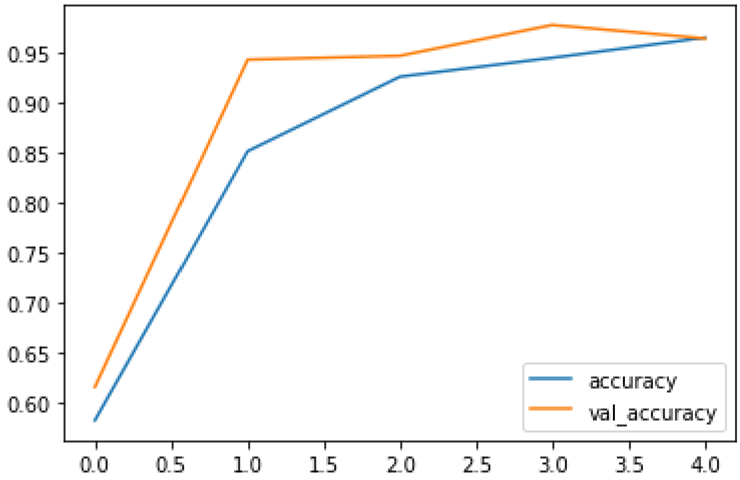

Fig. 5 Training and Validation Accuracy Change Curves

To further analyze the efficacy of the method proposed in this study, a fair comparison was conducted between the proposed model and five state-of-the-art models, namely ResNet-18, ResNet-50, VGG-16, Google-Net, and Inception-Net. Recognition accuracy was selected as the evaluation metric, and the results are presented in Table 1. Upon examination of Table 1, it can be observed that MobileNet-V2 outperforms the other models in terms of recognition accuracy.

Table 1. Comparison of recognition accuracy of different methods.

Models	Accuracy
VGG-16	95.32%
ResNet-18	95.68%
ResNet-50	97.54%
Google-Net	93.56%
Inception-Net	94.33%
MobileNet-V2	**98.27%**

To evaluate the lightweight advantage of the proposed approach, a comparison was made between the model parameters and computational requirements of the proposed method and the five advanced models mentioned earlier. The proposed method exhibits a lightweight advantage while maintaining precision, rendering it more amenable to practical applications. Table 2 presents the results of this comparison.

Table 2. Comparison of parameters and Flops of different methods.

Models	Params	Flops
VGG-16	138M	15.5G
ResNet-18	11.7M	1.8G
ResNet-50	25.6M	3.8G
Google-Net	7M	1.6G
Inception-Net	23.9M	5.7G
MobileNet-V2	**3.4M**	**0.3G**

Lastly, Table 3 showcases the time required for the proposed method and other methods to identify paddy diseases. It can be concluded that the inference recognition time needed by the proposed method is the shortest among the compared models, indicating its superior usability.

Table 3. Comparison of the time for different methods to identify Paddy's disease.

Models	Time
VGG-16	422ms
ResNet-18	397ms
ResNet-50	455ms
Google-Net	187ms
Inception-Net	231ms
MobileNet-V2	**75ms**

In summary, the paddy disease recognition algorithm based on MobileNet-V2, proposed in this study, demonstrates promising results in terms of recognition accuracy, model parameter quantity, and disease recognition time. This indicates its potential for practical application in the field of paddy disease identification and management.

4. Conclusion

In conclusion, this study has successfully developed a lightweight neural network model for rice disease classification using the MobileNet-V2 architecture, addressing the limitations of traditional identification methods that are manual, time-consuming, labor-intensive, and prone to misclassification. The proposed model's real-time identification capabilities on mobile devices facilitate prompt intervention and treatment of rice diseases, leading to improved crop yield and quality. Rigorous testing and benchmarking against state-of-the-art methods have demonstrated the exceptional performance of the designed method, outperforming existing techniques in accuracy and efficiency. The innovative approach of utilizing MobileNet-V2 in rice disease classification holds the potential to revolutionize rice cultivation by providing a powerful tool for farmers and agricultural professionals to monitor and manage diseases in real time. Future research could focus on further refining the model, exploring other lightweight neural network architectures, and integrating the technology with other agricultural management systems to optimize disease prevention and management in rice cultivation.

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