Paddy Doctor: A Visual Image Dataset for Paddy Disease Classification

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Abstract. One of the critical biotic stress factors paddy farmers face is diseases caused by bacteria, fungi, and other organisms. These diseases affect plants’ health severely and lead to significant crop loss. Most of these diseases can be identified by regularly observing the leaves and stems under expert supervision. In a country with vast agricultural regions and limited crop protection experts, manual identification of paddy diseases is challenging. Thus, to add a solution to this problem, it is necessary to automate the disease identification process and provide easily accessible decision support tools to enable effective crop protection measures. However, the lack of availability of public datasets with detailed disease information limits the practical implementation of accurate disease detection systems. This paper presents Paddy Doctor, a visual image dataset for identifying paddy diseases. Our dataset contains 13,876 annotated paddy leaf images across ten classes (nine diseases and normal leaf). We benchmarked the Paddy Doctor using a Convolutional Neural Network (CNN) and two transfer learning approaches, VGG16 and MobileNet. The experimental results show that MobileNet achieves the highest classification accuracy of 93.83%. We release our dataset and reproducible code in the open source for community use.

Keywords: Paddy Diseases · Deep learning · Transfer Learning.

1 Introduction

Agriculture is one of the most important industries contributing to the majority of the national income in several countries. In India, more than 60% of the population relies on agriculture [2]. Paddy is a ubiquitous crop in most Asian countries, and India is the world’s second-largest producer of paddy. Paddy cultivation is a complex process affected by many diseases and pests. The early identification of these paddy crop diseases is a daunting task for agriculturists as well as for agriculture experts [17]. Traditionally, farmers employ manual techniques based on their experience and visual inspection to identify the paddy diseases, but this is highly inefficient, time-consuming, and error-prone [20]. At times, even experienced farmers and agriculture experts might fail to identify the
crop diseases accurately due to the large variety of identical disease symptoms. Moreover, farmers apply a large quantity of fertilizer or pesticide without identifying the exact reason for disease manifestation, monitoring the depth of the disease, and measuring the micro-nutrient deficiency. Pesticides are well known for affecting both plants and the soil. It is increasingly important to automate the process of detection of the paddy disease at the earlier stage to reduce pesticide usage and subsequently minimize the loss in the yield \cite{21}.

With the advent of Information and Communication Technology (ICT), many researchers have proposed automated disease identification methods by leveraging computer vision techniques \cite{9}. While the traditional methods usually involve manual feature engineering, the recent deep learning-based approaches automatically extract and analyze image features and improve performance. Convolutional neural networks are one of the widely used techniques. Moreover, the variations of convolutional neural network architecture such as AlexNet \cite{22}, EfficientNet \cite{6}, Residual Networks \cite{23}, and DenseNet \cite{19} have enabled the machines to understand critical patterns from the diseased part of the leaf, delivering even better performances than human analysis in many classification problems. Despite all these efforts, the lack of availability of labeled data from real paddy fields hinders the proliferation of these techniques into practical use.

This paper presents 	extit{Paddy Doctor}, a large-scale annotated dataset for automated paddy disease identification. The paddy leaf images were collected from real paddy fields using high-resolution smartphone cameras. The collected images were carefully cleaned and annotated with the help of an agricultural officer (AO). The final dataset contains 13,876 leaf images across ten classes (nine diseases and healthy leaves). To validate the usefulness of our dataset, we benchmark the 	extit{Paddy Doctor} dataset using three state-of-the-art deep learning models, namely Deep Convolutional Neural Network (DCNN) and two transfer learning-based networks VGG16 and MobileNet. Our experimental results revealed that MobileNet achieved the highest classification accuracy of 93.83%. We release the 	extit{Paddy Doctor} dataset and reproducible code in the open source\footnote{https://paddydoc.github.io/}.

The rest of the paper is organized as follows. In section 2, we summarize the related works. Section 3 describes the dataset collection process and deep learning models for paddy disease identification. Section 4 presents the experimental setup and results, followed by a conclusion in section 5.

## 2 Related Work

Several researchers have proposed an automated identification system for rice disease detection. In \cite{11}, rice disease detection was accomplished by considering the area of the diseased leaf using image processing and a model was developed using the Naive Bayes Classifier. This classifier could identify three types of diseases of paddy plants with a prediction accuracy of 89%. In another study \cite{13}, the infected area was extracted using K-means clustering from the diseased leaf surface.
Table 1. Comparison of paddy disease datasets.

| Dataset                                           | Image resolution | No. of Images | No. of diseases and names of diseases. |
|---------------------------------------------------|------------------|---------------|----------------------------------------|
| Dharmsinh Desai University, India [13]            | 3081 x 897       | 120           | 3 - BLB, Brown spot, Leaf Smut         |
| Indonesia [1]                                     | 1440 x 1920      | 240           | 3 - Blast, BLB, Tungro                |
| Philippines [3]                                   | 300 x 300        | 552           | 3 - Blast, BLB, Brown spot            |
| Rice Leaf Diseases Data Set [4]                   | 3081 x 897       | 1,294         | 3 - BLB, Brown spot, Leaf Smut        |
| Malaysia [7]                                      | 4032 x 1908      | 2,400         | 3 - Blast, Brown spot, Hispa          |
| Nigeria [5]                                       | 256 x 256        | 3,355         | 3 - Blast, Brown spot, Hispa          |
| Sambalpur University, India [15]                  | 300 x 300        | 5,932         | 4 - BLB, Blast, Brown spot, Tungro    |
| Paddy Doctor                                      | 480 x 640        | 13,876        | 9 - BLB, BLS, BPB, Blast, Brown spot, Dead heart, Downy Mildew, Hispa, Tungro |

BLB: Bacterial Leaf Blight; BLS: Bacterial Leaf Streak; BPB: Bacterial Panicle Blight.

In recent years, deep learning techniques have been used to detect and classify rice diseases [14,21,18,12]. In [14], a CNN model was used to classify three types of rice diseases. The proposed CNN model has achieved an accuracy of 94.12%. In [21], the authors proposed an Attention-based Depthwise Separable Neural Network - Bayesian Optimization (ADSNN-BO) model that has achieved an accuracy of 94.65%. In [8], AlexNet model was used for rice disease identification and achieved an accuracy of 96.5%. In [12], CNN and Multilayer Perceptron (MLP) models were proposed to achieve 81.03% and 91.25% accuracy.

A relatively small dataset with fewer paddy diseases was used in most of the earlier works (See Table 1). In contrast, we present a large paddy leaf disease dataset containing 13,876 annotated images with ten classes (nine diseases and normal leaf) and benchmark the performance of three deep learning models.

3 Methodology

3.1 Data Collection

We collected RGB images of paddy leaves from real paddy fields in a village near the Tirunelveli district of Tamilnadu, India. We used the CAT S62 Pro smartphone that has inbuilt support for capturing both RGB and infrared images of the scene together. Our initial dataset contained more than 50,000 images, but we carefully examined each and excluded the noisy and redundant images.
After cleaning, we had 13,876 images. Next, we annotated each leaf image with the help of an agricultural officer into one of the nine disease categories and healthy leaves. The annotated paddy diseases are Bacterial Leaf Blight (BLB), Bacterial Leaf Streak (BLS), Bacterial Panicle Blight (BPB), Blast, Brown spot, Dead Heart, Downy Mildew, Hispa, Tungro, and Normal. Although the original images were 1080x1440 pixels, we transformed them into a low-resolution image of 480x640 pixels to facilitate the processing and development of models on desktop computers. Figure 1 shows the sample images of leaves having these nine diseases and healthy leave. In addition to the RGB images, we also manually collected additional metadata for each leaf image, such as the age and variety of the paddy crops.

3.2 Deep Learning Models

In this work, we apply three deep learning models to our Paddy Doctor dataset and compare their performance.

Deep Convolutional Neural Network: The architecture of the CNN model is shown in Figure 2. It consists of five 2D convolutional layers and a final dense layer. The first convolutional layer is filtered with 32 kernels of size 3 × 3. Then, a 3×3 max-pooling layer is added after the first convolutional layer. The next convolutional layer contains 64 convolution kernels of size 3×3. We have used a batch normalization layer to automatically standardize the inputs in a model and improve the accuracy and stability of neural networks. Similarly, the subsequent three layers use filters of sizes 64, 128, and 128, respectively. The last layer is
composed of a max-pooling layer. Two dense connectivity strategies improve the usage efficiency of feature maps, enhancing the diagnostic performance for paddy leaf diseases and a 10-way Softmax layer.

Transfer Learning: In addition to the CNN, we also apply two existing deep learning models to our dataset and evaluate their performance. Though the pre-training models can be used as feature extractors and predictors, we fine-tuned them to perform better. As shown in Figure 3, the fine-tuning approach involves keeping most of the existing pre-trained convolutional layers but training only the last few layers and the final fully connected layers. The selected pre-trained models are VGG16 and MobileNet. VGG16 is a widely used sequential network model with a depth of 16 layers. Whereas, MobileNet is specifically designed for mobile and embedded devices with a depth of 55 layers.

4 Experimental Setup and Results

We split the entire dataset into training and test sets. The training set consists of 10,407 (75%) images, and the test set had the remaining 3,469 images out
of 13,876 images. Image data augmentation was also performed during model training by applying different image transformation techniques. The operations include rotation ($5^\circ$), shear intensity ($0.2^\circ$), zoom ($0.2$), width and height shift ($0.05\%$) and horizontal flip. Moreover, all images were resized into 256x256 pixels and normalized. All models used a learning rate of 0.001, 25 epochs, and 32 batch sizes for training. We use the standard classification accuracy to measure and compare the performance of the models.

The implementation of the deep learning models was done in Python using Keras and TensorFlow libraries. We used Google’s Colab framework using GPU to conduct all the experiments. The training process took approximately 90 minutes for each model. The experimental results showed that MobileNet achieved the highest classification accuracy of 93.83%. This is followed by VGG16, achieving 93.66%. In comparison, the DCNN model achieved the lowest accuracy of 87.97%. These results demonstrate the usability of the dataset for automated paddy disease classification tasks. We plan to evaluate additional pre-trained models based on different transfer learning strategies in the future.

5 Conclusion

Manual identification of paddy diseases is a challenging task for farmers. Hence, there is an increasing need to develop automated solutions that can scale to many diseases and plants. The lack of availability of public datasets with annotated disease names was a major bottleneck to benchmarking the recent deep learning-based models and wider adoption of the solutions. In this paper, we presented the Paddy Doctor dataset for automated paddy disease detection. It contains 13,876 annotated paddy leaf images across ten classes (nine diseases and normal leaf). The presented dataset was benchmarked using three deep learning-based models and we compared their performance across each other. The results demonstrate that MobileNet achieved a superior accuracy of 93.83% followed by 93.66% with VGG16 based model.

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