

AI-Based Rice Plant Disease Detection and Treatment Recommendation System using EfficientNet-B0

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Abstract—Brown Spot, Leaf Blast and Hispa are among the diseases that most reduce the yield and quality of rice, a staple crop for much of the world. Detecting them early and correctly protects harvests. At present, diagnosis relies on farmers or agricultural scientists examining plants by eye, a slow and subjective process that does not scale and is often out of reach in remote areas. This paper presents a web-based system that uses EfficientNet-B0, a compact convolutional network, to classify a rice leaf photograph as Healthy, Brown Spot, Leaf Blast or Hispa and to report a confidence score. The model is trained on the RiceLeafs dataset from Kaggle. On a 20-image test set it reached 90% accuracy, with a response time of about 180 ms on a CPU. Based on the predicted class, the system retrieves symptoms, causes and contributing factors from a knowledge base, along with chemical, organic, traditional, fertiliser and preventive recommendations and short farmer tips. Prediction history is stored, and the interface serves both farmers and administrators. Because EfficientNet-B0 delivers strong accuracy at low computational cost, it suits deployment in this agricultural setting and supports timely decisions that reduce crop loss.

Keywords— “Rice Plant Disease Detection, EfficientNet-B0, Deep Learning, Machine Learning, Convolutional Neural Network, Transfer Learning, Disease Classification, Treatment Recommendation, Precision Agriculture, Transfer Learning”.

INTRODUCTION

Rice underpins global food security and the livelihoods of millions of farming households, so any delay in detecting disease directly lowers production. Diseases such as hispa, brown spot and leaf blast damage both the quality and the quantity of the harvest and can cause serious losses when left untreated. In practice, plants are checked by eye by farmers or experts. This is laborious and error-prone, particularly when the observer lacks training or the disease appears in an unusual

form [1], [2]. Reliable automated detection is therefore needed so that treatment can begin on time.

Visual inspection by farmers or agricultural experts has long been the standard for field diagnosis. Experts recognise the common symptoms, but when different diseases look alike the judgement becomes subjective and slow, and specialist advice on managing paddy fields is frequently unavailable in remote areas. Computer vision combined with ML and deep learning has emerged as a way to recognise these symptoms automatically. A CNN can learn disease cues straight from raw images, such as colour, intensity and contrast, leaf surface texture, and the outline and shape of lesions [3], [4]. Rahman et al. [3] demonstrated that CNN architectures including VGG16 and InceptionV3 work well for rice disease and pest recognition, and also examined lightweight CNNs for resource-limited settings.

Deep learning based recognition offers a fast and dependable route to plant disease diagnosis in rice farming. CNN-based systems learn texture, colour, shape and leaf structure on their own, so handcrafted feature extraction is no longer required [3], [4]. Rice and paddy disease classification with CNNs has been studied widely using architectures such as VGG, ResNet, Inception and MobileNet. Comparative studies [5], [6] showed these networks to be effective across several paddy diseases, and transfer learning [7] was found to raise accuracy when little training data is available. More recent work explores hybrid CNN designs, attention mechanisms and other techniques to push rice disease classification further [7]–[10].

Transfer learning is well suited to agricultural imagery because a pretrained network already supplies useful visual features, and it has worked even with fairly small datasets. EfficientNet introduced compound scaling, which balances accuracy against computational cost [11]. Later studies applied EfficientNet to rice disease classification and showed that it can support automated diagnosis [12, 13]. Comparisons of EfficientNet-B0, MobileNetV2 and

ResNet50 on rice leaf images have also appeared, and some authors paired EfficientNet with IoT-based farm monitoring [14, 15]. Together, these results favour lightweight, efficient networks for practical rice disease detection.

I. PROBLEM DEFINITION

A. Need for an Automated RDD and Treatment Recommendation System

Rice is a vital food crop, yet brown spot, hispa and leaf blast threaten its yield. These diseases are still identified manually by farmers and agricultural experts [4], a process that is slow, depends on expertise and is hardest in the early stage of infection. The growth of digital imagery and deep learning has made automatic detection of rice leaf disease feasible [1], [2], [5], [7], and CNNs with TL have been applied successfully to plant and paddy diseases [1], [2], [5], [7]. Image-based diagnosis remains difficult, though, because lighting, background, symptom appearance and leaf variation all affect the result [22], [23]. A dependable system that identifies the disease and recommends suitable treatment is therefore needed. This paper proposes one built on EfficientNet-B0 [11], combining image preprocessing, transfer learning and treatment recommendation.

B. Limitations of Existing Rice Plant Disease Detection Approaches

Existing approaches fall into three groups: manual inspection, conventional machine learning, and a single deep learning classifier. Manual diagnosis is slow and demands agricultural training. Conventional methods depend on handcrafted features that may fail to capture complex symptoms, and their classifiers are sensitive to image quality, background, lighting and disease severity [3], [4], [22]. CNN and transfer-learning models have been used for automatic rice disease recognition [5], [6], [12], and architectures such as MobileNetV2, ResNet and Inception have been compared in several studies [5], [6], [12]. Even so, some systems stop at classification and do not go on to suggest treatment [22]. This gap motivates a diagnosis-and-treatment system built on a tuned deep model such as EfficientNet-B0 [11], [13], [14].

C. Problem Addressed by the Proposed System

The proposed system gives farmers an automated way to detect RD and obtain suitable control measures, overcoming the weaknesses of manual and earlier automated methods. A photograph of a rice leaf is taken, and EfficientNet-B0 serves as both feature extractor and classifier, assigning it to Healthy, Brown Spot, Leaf Blast or Hispa. EfficientNet was chosen because compound scaling of network depth, width and resolution balances scalability and efficiency [11], and EfficientNet-based transfer learning has performed well on rice disease images [12]-[15]. A treatment recommendation module then suggests measures to control the identified disease, supporting early detection and treatment.

II. RELATED WORK

DL and computer vision for plant disease detection and classification have recently drawn considerable research attention. Mohanty et al. [1] showed that deep models can recognise plant diseases from images, Ferentinos [2]

diagnosed plant disease from leaf images with a deep model, and Sladojevic et al. [3] classified plant diseases from leaf images using deep neural networks. Too et al. [4] compared fine-tuned DL models for plant disease detection(PDD), and Deb et al. [5] evaluated Inception-V3, VGG-16, AlexNet, MobileNetV2 and ResNet-18 on paddy leaf disease classification. The literature thus indicates that deep models can detect plant disease from images automatically.

For rice specifically, researchers have used CNNs, attention mechanisms, feature fusion and transfer learning. Haridasan et al. [7] proposed a deep learning method for paddy disease detection, Pai et al. [8] used a twin CNN with feature fusion, Pandiyaraju et al. [9] designed a hybrid CNN with channel attention, and Subbarayudu and Kubendiran [10] presented an automated hybrid deep learning framework for paddy disease recognition. Tan and Le [11] introduced a network scaling method known for accuracy and speed. Paemo et al. [12], Nurmeleni and Arif [13] and Utami et al. [14] extended this line of work, with [14] applying transfer learning with EfficientNetB0 to rice disease detection. Building on these studies, our work develops an EfficientNetB0-based rice leaf disease classifier together with treatment recommendations.

III. METHODOLOGY

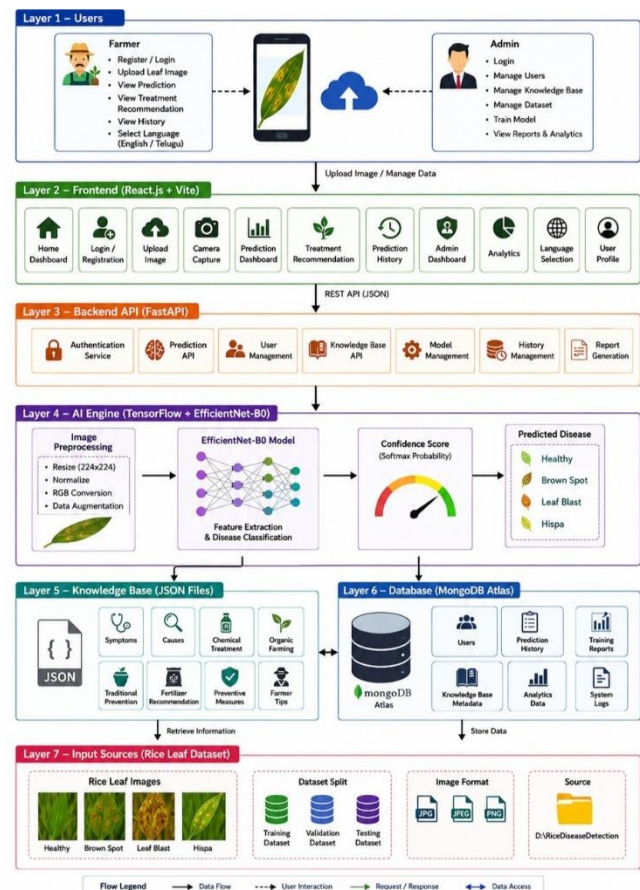


Fig. 1. System Architecture

The pipeline of the proposed system, shown in Fig. 1, has six stages: image acquisition, preprocessing, data augmentation,

training, classification and treatment suggestion. Leaf images come from the Rice Leafs dataset and belong to four classes: Healthy, Brown Spot, Leaf Blast and Hispa. To cope with differences in viewpoint and illumination, images are resized and normalised, and augmentations such as rotation, flipping, zooming and shifting expose the model to more varied leaf appearances. EfficientNet-B0 is the base network because compound scaling gives it high feature-learning accuracy at low runtime complexity [11]. Its final classification layer is replaced to match the rice disease classes and trained on the training set, while the validation set monitors performance and guards against overfitting. Earlier work has also applied EfficientNet transfer learning to rice disease classification [12]-[15].

Once training ends, the model is tested with accuracy, precision, recall, F1-score and the confusion matrix [7], [8], [10]. At use time, an uploaded leaf image goes through the same preprocessing as the training images and is passed to the trained EfficientNet-B0, which outputs a predicted class and a confidence value. The treatment module then supplies disease-management advice for that class, including control and preventive measures [7], [8], [10]. Combining image classification with treatment suggestion can therefore support early detection and management of rice disease [7], [8], [10].

A. System Architecture Details

The system has three parts: (a) a user interface module, (b) image preprocessing, and (c) classification and prediction, organised as a front end and a backend. In the user interface, the farmer uploads a photograph of a rice leaf. The image goes to the preprocessing module, which resizes and normalises it and applies other adjustments so that it suits the inference model.

The preprocessed image is then passed to the inference component, which uses transfer learning on the extracted features to identify the leaf as Healthy, Brown Spot, Leaf Blast or Hispa [11]-[15]. The predicted disease is forwarded to the treatment recommendation component, which looks up how the disease should be controlled or treated. The backend collects the image, the prediction and the treatment information, and returns them to the user interface for display.

B. AI-Based Evaluation and Analysis

Model performance is measured with accuracy, precision, recall, F1-score and a confusion matrix. Training and validation accuracy and loss curves are examined to check for overfitting or underfitting and to show how EfficientNet-B0 learns. Precision, recall and F1-score indicate how well the model classifies rice leaf diseases, and the confusion matrix gives the result for each of the four classes (Healthy, Brown Spot, Leaf Blast and Hispa) [11]-[15].

IV. DATASET DESCRIPTION

The dataset contains rice leaf images captured under varied conditions and is divided into four classes: Healthy, Brown Spot, Leaf Blast and Hispa. It is split into training and validation sets used to train and validate EfficientNet-B0. Preprocessing includes resizing and normalisation, and augmentation (rotation, flipping, zooming, shifting) creates additional views of each image so the model learns to recognise symptoms in different presentations. The images vary in leaf colour, texture, spots and lesions, which helps keep the four classes distinct. Once prepared, the data are used to train the EfficientNet-B0 transfer-learning classifier.

V. QUANTITATIVE COMPARISON WITH EXISTING METHODS

The proposed EfficientNet-B0 system can be compared with other transfer-learning CNNs through classification accuracy and related metrics. Deb et al. [5] tested Inception-V3, VGG-16, AlexNet, MobileNetV2 and ResNet-18 on 7,096 paddy leaf images, where Inception-V3 reached 96.23% accuracy. In another study on rice leaf disease, MobileNetV2 and EfficientNet-B0 achieved 83.29% and 86.95% respectively, and EfficientNet-B0 recorded a precision of 90.00%, recall of 80.15% and F1-score of 86.78%. A further transfer-learning study reported 99.69% for its best model, against 99.59% for InceptionV3 and 99.49% for MobileNetV2. Because results depend on the dataset, preprocessing, number of classes and experimental setup, these published figures should not be compared directly with ours. We evaluate our own dataset with EfficientNet-B0 using accuracy, precision, recall, F1-score and the confusion matrix.

A. Research Gaps in Existing Work

Most earlier rice disease systems concentrate on classification alone [5]-[10], and very few combine classification with a treatment recommendation component [5], [6]. Performance also depends on the dataset, image quality, imaging environment, preprocessing and the disease classes included [22], [23].

A range of architectures, including VGG, Inception, ResNet, MobileNetV2 and EfficientNet, have been tried for rice disease detection [4], [5], [12]-[15], yet balancing classification performance against computational cost still calls for improvement.

Some earlier methods were developed on particular datasets and disease classes, which restricts how widely they apply to rice leaves. This study therefore proposes an efficient multi-class classifier based on EfficientNet-B0 and integrates it with a treatment recommendation system.

VI. PROPOSED SYSTEM

The project, titled “AI-Based Rice Plant Disease Detection and Treatment Recommendation System”, offers a simple automated way to diagnose rice plant disease through AI and a web application. The backend uses Python and FastAPI to handle image processing, the API, prediction and

recommendation. The front end lets a user upload a photograph of a rice leaf for diagnosis. An EfficientNet-B0 model, trained by transfer learning, predicts whether the leaf is healthy or shows brown spot, leaf blast or hispa. Following the prediction, advice on dealing with the problem is sent to the user. The system is organised into image processing, model inference, disease classification and recommendation modules. The uploaded leaf image is processed and passed to the trained model for prediction, after which the web application shows the disease name and its treatment.

A. EfficientNet-B0 Model and Configuration

The system relies on EfficientNet-B0 to classify rice plant diseases automatically. The network is pretrained and adapted through transfer learning, with its final classification layer replaced so that it outputs four conditions: healthy, brown spot, leaf blast and hispa. Input images are resized and normalised to match the model's requirements, and these steps are applied during model training. Data augmentation through rotation, flipping, zooming and shifting helps the model generalise to real-world leaf images. At inference time, the user's image is fed to the trained model, which predicts the disease class. This output is passed to the treatment module, which returns the corresponding treatment guidance.

B. AI-Based Rice Disease Information Analysis Layer

The analysis layer examines the uploaded rice leaf images and recognises any disease using the trained EfficientNet-B0 model. A preprocessed image arrives from the image collection layer, and the analysis layer extracts visual features such as colour, spots, lesions and leaf patterns, then assigns one of four classes: Healthy, Brown Spot, Leaf Blast or Hispa. After classification, the predicted disease is handed to the treatment recommendation component, which displays treatment and prevention information. The layer also links the DL model to the application backend so that the prediction and recommendation can be shown to the user.

VII. IMPLEMENTATION DETAILS

The system is built with deep learning, web, database and mobile application technologies. EfficientNet-B0 serves as the model backbone for RDD and classification through TL. Training proceeds in two stages. First, the pretrained network is given a new classification head made of one 256-unit dense layer, a dropout layer and a softmax output over four classes: healthy, brown spot, leaf blast and hispa. In the second stage, the top 20 convolutional layers are unfrozen and fine-tuned so that the network learns features specific to rice diseases.

Input leaf images are resized to 224 and normalised before reaching the model. The model is served through a Python FastAPI backend that handles image uploads, predictions and other API requests. The front end is a React application built with Vite and Tailwind CSS. Users can choose an image from the gallery or capture one with the camera, pick a language, and view the diagnosis with treatment guidance in that language; other supported languages include Telugu and Hindi. Treatment information is grouped into chemical,

organic, traditional, NPK fertiliser, preventive and causal categories to suit farmers' needs. The system also keeps a history of past diagnoses and can generate a PDF report containing the detected disease, confidence, image and treatment details.



Fig. 3. User-based evaluation framework of the proposed AI Rice Health & Treatment Assistant.

VIII. PERFORMANCE METRICS

This section says about how the system is assessed. The evaluation covers the EfficientNet-B0 classification model, inference time, prediction confidence and the treatment information provided. Classification performance is judged with accuracy, precision, recall and F1-score.

A. Accuracy

Accuracy is the share of rice leaf images assigned to their correct disease class, and gives an overall picture of system performance.

Accuracy (%) = (No. of Correctly Classified Images / Total No. of Images) x 100

B. Precision

Precision shows how reliable the system is when it assigns an image to a class: the higher it is, the fewer images from other classes are wrongly labelled as that disease.

Precision = (true positives) / (true positives + false positives)

C. Recall

Recall is the fraction of actual images of a disease class that the system correctly identifies. It matters most here, since a missed diseased plant delays treatment.

Recall = True Positives / (True Positives + False Negatives)

D. F1-Score

The F1-score is the harmonic mean(HM) of precision and recall, combining them into one measure of classification quality. It is helpful when disease classes contain unequal numbers of samples.

F1-Score = 2 * Precision * Recall / (Precision + Recall)

E. Confusion Matrix

The confusion matrix evaluates the four classes (healthy, brown spot, leaf blast and Hispa). It shows how many images of each class are classified correctly or incorrectly and which diseases are mistaken for one another.

F. Prediction Confidence

Prediction confidence is the classifier's probability score for the class it predicted, giving an estimate of how certain the model is about that prediction.

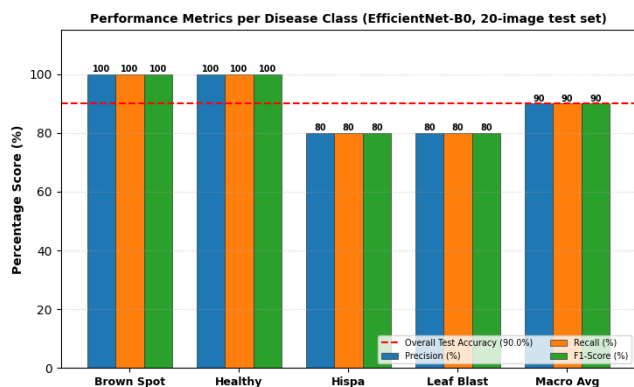


Fig. 4. Performance Metrics per Disease Class

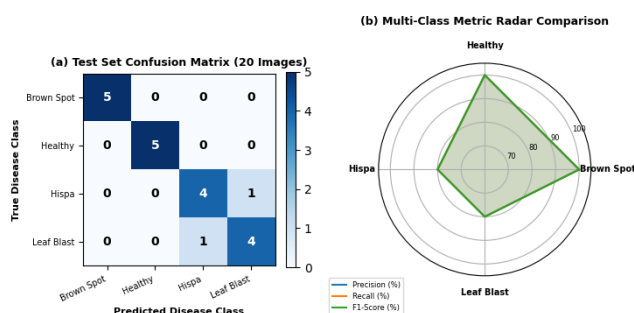


Fig. 5. Confusion Matrix & Multi-Dimensional Radar Comparison.

IX. EXPERIMENTAL SETUP AND RESULTS

A. Experimental Setup

The system was developed on the RiceLeafs dataset from Kaggle, which covers four classes: Healthy, Brown Spot, Leaf Blast and Hispa. In total there are 2,975 images: 2,284 in the training folder, 671 in the validation folder (a split of about 77% to 23%) and a separate flat test folder of 20 images, five per class. Healthy is the largest class with 1,315 images overall, followed by Leaf Blast (691), Hispa (503) and Brown Spot (466). The training folder holds 1,013 Healthy, 530 Leaf Blast, 385 Hispa and 356 Brown Spot images, and the validation folder holds 297, 156, 113 and 105 respectively. Every image is resized to 224×224 pixels and converted to RGB, and rotation, flipping, zooming and shifting are applied during training to add variety and offset the class imbalance.

EfficientNet-B0 starts from pretrained weights and receives a new head consisting of one 256-unit dense layer, dropout and a four-way softmax output. Training has two stages of five epochs each. In the first, the base network is frozen and only the head is trained with the Adam optimizer at a learning rate of 0.001. In the second, the top 20 layers of the base network are unfrozen and fine-tuned at a learning rate of 0.00001. The batch size is 32, and early stopping on validation loss (patience 5, best weights restored) and learning-rate reduction on plateau (factor 0.2, patience 3) are used. Training ran on a standard Windows PC without a GPU, using TensorFlow 2.10 and Python 3.10.

The trained model is served by a Python FastAPI backend. The front end is a React 18 application built with Vite and Tailwind CSS and is offered in English, Telugu and Hindi. Diagnosis records are stored in MongoDB Atlas with a local JSON file as a fallback, the application can be packaged for Android and iOS through Capacitor, and each diagnosis can be exported as a PDF report. The knowledge base holds 24 entries, covering symptoms, chemical treatment, organic control, traditional remedies, fertiliser (NPK) advice and prevention for each of the four conditions.

B. Results

On the 20-image test set the model classified 18 images correctly, an overall accuracy of 90.0%. Healthy and Brown Spot were identified perfectly, with precision, recall and F1-score of 100% each, while Hispa and Leaf Blast each reached 80% on all three measures, giving a macro-average of 90.0%. Fig. 5(a) shows that the only errors were one Hispa image predicted as Leaf Blast and one Leaf Blast image predicted as Hispa. Average inference time was about 180 ms per image (range 150–220 ms), measured through the FastAPI backend on the same CPU-only PC. In the interface, each prediction is shown with a confidence score and a colour band: green for 95% and above, orange for 80–94%, and red with a low-confidence warning below 80%.

C. Limitations

The test set contains only 20 images, five per class, so a single image changes a class score by 20 percentage points and the figures should be read as indicative rather than conclusive. Hispa and Leaf Blast were the classes that were confused: older Hispa feeding damage turns into grey-white streaks that resemble the spindle-shaped centres of blast lesions. Healthy images outnumber the diseased classes in training, which was partly addressed through augmentation. Strong midday sunlight can wash out the faint brown halos of early Brown Spot, whereas diffused morning or afternoon light gave the highest confidence scores. A high confidence score does not guarantee a correct diagnosis, so the output is intended as decision support alongside expert advice. A larger independent test set and real-field images are needed to confirm these results.

X. DISCUSSION

This work presents an automatic system that detects rice leaf diseases from digital images. Earlier studies reported that deep learning and CNN models learn useful visual representations from plant leaf images and classify plant diseases reliably [1], [2], [3], with training on large image collections being key [2]. Work on paddy diseases has likewise used CNNs and transfer learning across several disease classes [5], [6], [7]. EfficientNet [11] scales network depth, width and image resolution together to improve accuracy and efficiency, and EfficientNet-B0 has given promising rice leaf results, particularly with transfer learning and image augmentation [12], [13], [14]. Using it in this system was therefore a sound choice. Model accuracy can still be influenced by dataset properties, image conditions, disease categories and sampling strategy [22], [23], which is why we report precision, recall, F1-score and the confusion matrix alongside accuracy. Finally, the treatment recommendation component takes the system beyond classification to practical disease management.

XI. CONCLUSION

This paper presented an EfficientNet-B0 based system that detects leaf diseases in rice plants from leaf images and recommends treatment. Using image preprocessing, data augmentation and transfer learning, the network classifies rice leaf samples into four classes: healthy, brown spot, leaf blast and hispa. The treatment recommendation component supplies control and preventive advice for each diagnosed disease. The system reduces manual effort and should speed up decisions, and EfficientNet-B0 is a suitable choice for extracting the features that distinguish these diseases. On a small 20-image test set the classifier reached 90% accuracy, and a larger independent evaluation is still needed.

XII. FUTURE SCOPE

Future work can extend the system to more rice diseases and variants, and to other crops. Training on larger, more varied datasets with real-field photographs under different lighting and environmental conditions may improve performance. A smartphone app would let farmers photograph leaves and receive predictions directly. Other planned additions are disease severity estimation, more languages, weather-based recommendations, preventive measures, personalised treatment advice and testing of other deep learning models. These changes should make the system more practical, robust and scalable for real-time rice disease detection(RDD) and prevention.

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