

AI Based Paddy Disease Prediction System

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ABSTRACT - More over half of the world's population relies on paddy, but illnesses hinder its production. These illnesses must be diagnosed early and accurately to reduce yield losses and apply control measures. This research provides an AI-based method for leaf image-based prediction and categorisation of prevalent paddy illnesses. The method uses a deep Convolutional Neural Network (CNN) to recognise Brown Spot, Leaf Blast, and Hispa visual symptoms. A custom dataset of paddy leaf images is used to fine-tune a pre-trained EfficientNet model via transfer learning. The model is tested for disease classification and leaf health. The system's high accuracy makes it a powerful, low-cost, and easy diagnostic tool for farmers to make faster and more educated crop protection decisions.

Keywords—Paddy Disease, Rice Disease, Deep Learning, Artificial Intelligence, Convolutional Neural Network (CNN), Image Classification, Precision Agriculture, Transfer Learning.

I. INTRODUCTION

Rice (*Oryza sativa*), also known as paddy, feeds billions. World population growth drives rice consumption. Rice production is threatened by many biotic stressors, including plant diseases, which reduce yield. Brown Spot, Leaf Blast, and Hispa can spread quickly through a field, damaging crops and costing farmers money. Traditional paddy disease management involves farmers or agricultural extension agents visually inspecting plants. Several considerations make this process difficult. First, untrained eyes can misdiagnose diseases due to similar visual symptoms. Second, in isolated agricultural areas, specialist expertise is scarce. Ineffective, economically wasteful, and environmentally hazardous fungicides and insecticides may be used due to diagnosis delays or inaccuracies. Recent advances in AI, particularly in computer vision, provide a transformative answer. This research offers an AI-based system that employs deep learning to automatically identify paddy leaf diseases from digital images. Train a strong Convolutional Neural Network (CNN) on a labelled dataset of ill and healthy leaves to recognise each condition's visual patterns. The ultimate goal is to create a mobile app that gives farmers rapid, reliable diagnostics in their fields.

II. RELATED WORK

Using computational methods to diagnosis plant diseases is a growing subject in precision agriculture. Early studies used standard image processing and machine learning methods. First, image processing techniques such colour space translation (e.g., RGB to HSV) and thresholding were used to segregate the suspected lesion area from healthy leaf tissue [1]. To quantify lesion visual properties, handmade features would be extracted after segmentation. These features comprised colour histograms, texture (Gray-Level Co-occurrence Matrix), and form (area, perimeter, circularity) [2]. These features were then loaded into a typical machine learning classifier like an SVM or k-NN to predict illness class. These algorithms provided a proof of concept, but they struggled with real-world field photographs' illumination, backdrops, and overlapping foliage. A paradigm change occurred with deep learning. Without manual feature engineering, Deep Convolutional Neural Networks (CNNs) may automatically train a rich hierarchy of discriminative features from raw pixel data, making them highly effective at image classification. CNN designs like AlexNet, VGGNet, and ResNet performed well on general-purpose benchmarks [3], inspiring their use in agriculture. Many studies have used CNNs to detect illnesses in tomato, maize, and apple crops [4]. Multiple studies have shown that CNNs can accurately classify paddy

illnesses such Leaf Blast, Brown Spot, and Bacterial Blight [5]. Transfer learning is a successful and popular method in this area. This entails fine-tuning a CNN model pre-trained on ImageNet for paddy disease classification. This method uses the powerful, generic feature detectors from the huge dataset to work well with a somewhat sized, specialised dataset. Our work relies on this effective transfer learning approach to construct an accurate and practical diagnostic system.

III. METHODOLOGY

The proposed system is developed following a structured deep learning pipeline, which includes data collection and preparation, model selection and training, and rigorous evaluation.

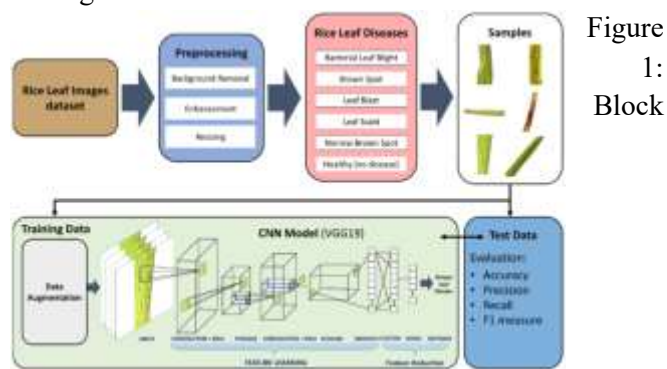


Figure 1:
Block

diagram

A. Preprocessing/Dataset

A well-labeled, high-quality dataset underpins supervised learning.

Data Collection: Paddy leaf photos from agricultural fields or public repositories are used to train the system. Agricultural professionals curate and label the dataset into 'Leaf Blast', 'Brown Spot', 'Hispa', and 'Healthy' classes.

Before being input into the CNN, images undergo numerous pre-processing stages. They are scaled to 256x256 pixels to match the model's input layer. Standardising pixel values to [0, 1] ensures robust and efficient training.

We use data augmentation to increase the model's generalisation and prevent overfitting to the training data. Applying random changes to images during training artificially extends the training set. These include horizontal/vertical flips, random rotations, zooming, and brightness/contrast adjustments. The model must learn the essential aspects of each disease regardless of image capture and slight differences.

CNN Architecture and Transfer Learning AI Model

A transfer learning-trained deep CNN powers our

prediction system.

Model Selection: We use EfficientNet, a cutting-edge CNN architecture [6]. EfficientNet models are suited for mobile devices since they are accurate and computationally less costly than ResNet.

Transfer Learning:

1. We create an EfficientNet model (e.g., EfficientNetB3) with pre-trained weights on ImageNet. Edges, colours, and textures are encoded in these pre-trained weights.
2. We delete the top classification layer from the model, which was created for 1000 ImageNet classes.
3. A custom categorisation head is added to the underlying model. This head usually has a Global Average Pooling layer, a Dropout layer for regularisation, and a Dense (fully-connected) layer with Softmax activation. The Softmax layer has output neurones equal to our paddy illness classes (four in this case).

The model is then fine-tuned on our paddy disease dataset. Training the network with a low learning rate lets pre-trained weights adapt to paddy leaf disease visuals.

C. Model Training + Evaluation

Adam optimiser and categorical cross-entropy loss function train the model. Its performance is critically assessed on a held-out test set (data not seen during training). We utilise these standard categorisation metrics:

Image classification accuracy: Percentage.

Precision, Recall, and F1-Score: These metrics are produced for each class to assess the model's performance, notably for disease identification.

Confusion Matrix: Shows right and wrong predictions for each illness class to visualise performance. This shows if the model is conflating diseases.

IV. RESULTS ANDDISCUSSION

This section presents the performance of the trained AI-based system for paddy disease prediction.

A. Quantitative Performance

The model's diagnostic accuracy is summarized quantitatively.

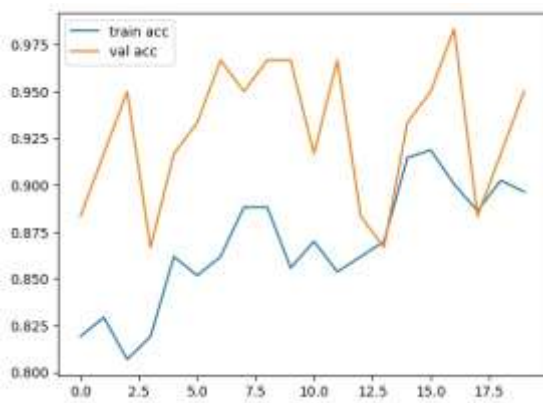


Figure 2: Accuracy of the model



Figure 3: Disease prediction

DISCUSSION

The experiments show that deep learning-based paddy disease prediction works. The CNN model acquired sophisticated visual characteristics to distinguish disease signs, as shown by its remarkable accuracy. However, the system has numerous practical constraints:

The model only predicts the diseases it was trained on. It cannot detect uncommon disorders.

Image Quality: Input image quality matters. Out-of-focus pictures, poor lighting, and intricate backdrops with overlapping foliage might hurt the model.

Early-Stage Detection: The algorithm may struggle to detect diseases with unclear visual indicators.

Environmental Factors: The approach ignores humidity, temperature, and soil type, which can indicate disease risk.

V. CONCLUSION AND FUTURE WORK

This research introduces an AI-based approach for paddy disease prediction and classification. A cutting-edge Convolutional Neural Network is fine-tuned on a leaf image dataset to achieve excellent diagnostic

accuracy. This technique could help farmers diagnose crop diseases earlier and more accurately, allowing them to intervene and protect yields.

Further development will improve the system's capabilities and holisticality:

Mobile Application Deployment: Optimising the model with TensorFlow Lite and creating an intuitive mobile app for farmers to use offline in the field.

Recommendation System Integration: Creating a knowledge-based module that recommends regionally available insecticides, fungicides, or cultural treatments for the projected disease.

Severity Estimation: Using picture segmentation to calculate the disease's leaf area % can help determine treatment intensity.

Advanced Multi-Modal Prediction Model: Integrating picture data with weather forecasts and soil sensor data to predict disease outbreaks before visual signs develop.

VI. REFERENCES

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