

Nutrition Deficiency In Paddy Leaf Using Neural Network

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ABSTRACT

Rice (*Oryza sativa*) is a primary food crop worldwide and is vulnerable to several foliar diseases that reduce yield. This manuscript proposes a unified, hybrid approach that combines YOLOv8 for real-time localization of symptomatic regions with a lightweight CNN classifier (transfer-learned EfficientNetB0/MobileNetV2) for fine-grained disease classification. The pipeline accepts field images of paddy leaves, performs robust preprocessing and augmentation, uses YOLOv8 to detect candidate lesions, crops and normalizes these regions, and classifies each region into one of four consistent disease classes: Healthy, Leaf Blast, Brown Spot, and Bacterial Leaf Blight. We describe dataset preparation, annotation conventions, model architectures, training strategies, and evaluation metrics (mAP, precision, recall, F1, confusion matrix). The proposed hybrid design preserves YOLOv8's real-time detection capability while improving classification accuracy on small lesions and visually similar disease symptoms. We provide a clear experimental protocol, recommended hyperparameters, and templates for figures and tables to ensure reproducible and professional presentation.

Index Terms— Rice, YOLOv8, Convolutional Neural Network (CNN), object detection, disease classification, data augmentation, precision agriculture.

I. INTRODUCTION

Rice is among the world's most important staple crops. Timely identification of foliar diseases such as leaf blast, brown spot, & bacterial blight is essential to mitigate yield loss. Manual inspection is time-consuming, inconsistent, and often unavailable in rural settings. Automated image-based diagnosis enables scalable, rapid, and repeatable detection.

This paper presents a single, coherent system that unifies YOLOv8-based detection and a compact CNN-based classifier. YOLOv8 serves as the real-time detector to localize diseased regions in field images; a separate lightweight CNN classifies the localized regions to increase per-lesion accuracy. This hybrid pipeline combines the strengths of both approaches while avoiding inconsistent claims about the number of classes, performance metrics, and model objectives.

Key contributions:

A unified, reproducible hybrid pipeline (YOLOv8 + CNN) for rice leaf disease detecting & classifying.

A careful methodology for dataset curation, annotation, preprocessing, and augmentation tailored to lesion detection and small-object classification.

Clear evaluation protocol and professional figure/table templates for rigorous reporting and reproducibility. Rice (*Oryza sativa*) is crucial food crops in the world, particularly in Asia, where it serves as a dietary staple for billions. However, rice cultivation is frequently threatened by various plant diseases, including leaf blast, brown spot, and bacterial blight, which can drastically reduce crop yield and affect food security. Traditionally, farmers rely on visual inspection and expert consultation to identify these diseases, which is not only time-consuming and inconsistent but also inaccessible in many rural or underdeveloped regions.

Computer vision and DL have recently made great strides, providing potential new options for the identification of plant diseases. Because of its inherent capacity to gather and learn hierarchical features from visual input, CNNs stand out among them as being very successful for picture categorization tasks. CNNs are able to generalize well across many situations, including illumination, orientation, and noise from background in leaf photos, and they also remove requirement for human feature extraction.

In this study, we provide a CNN-based automated disease detection system for rice plants that is as per DL. Program can accurately detect numerous diseases after being trained on a collection of tagged photos of rice leaves. This method may help farmers and agricultural specialists make better choices quicker by streamlining procedure of disease identification. This will help safeguard crops and enhance agricultural results.

The integration of CNN-based detection with mobile or embedded platforms could revolutionize modern precision agriculture by providing real-time, on-site disease diagnosis without requiring sophisticated lab equipment or expert intervention. Zhang et al. (2020) used a modified ResNet model to classify rice diseases from field images,

highlighting the robustness of CNNs in real-world noisy environments. To address the challenge of detecting small lesions, Chen et al. (2021) suggested a CNN design with several scales that may capture coarse and fine characteristics, enhancing symptom identification performance in the early stages.

To help farmers diagnose rice diseases in real-time, Lu et al. (2021) presented an IoT smart agricultural system that combines mobile devices with CNN disease detection. As an added bonus, Karthik et al. (2022) used EfficientNet, a CNN model that is both lightweight and strong, to identify diseases in rice leaves. They were able to obtain high accuracy while reducing the computational complexity, which makes it a good fit for mobile platforms.

Recent research by Rani et al. (2023) focused on dataset curation and CNN model benchmarking using a large-scale rice leaf disease image dataset. Their experiments validated that data augmentation and dropout techniques significantly enhance the model's generalization capability. Furthermore, Zhao et al. (2024) applied attention mechanisms within CNNs to localize diseased regions more effectively, improving the interpretability and accuracy of the model.

Collectively, these studies affirm that CNNs are highly effective for rice disease detection, particularly when combined with transfer learning, multi-scale features, and mobile integration. The literature strongly supports the use of deep learning as a scalable, accurate, and automated solution to assist farmers in combating crop diseases. This project focuses on developing an automatic paddy leaf illness detecting system utilising YOLOv8. The system processes paddy leaf images, identifies infected regions, and classifies disease categories with bounding boxes in real time. By leveraging YOLOv8's advanced architecture, the model eliminates the need for handcrafted features and instead learns directly from raw images, making it robust against variations in lighting, leaf texture, and background conditions.

An intelligent, affordable, and flexible approach for early identification of diseases is what suggested system is all about for farmers. This method improves crop management and output by decreasing reliance upon agricultural specialists and increasing the speed of decision-making.

II. LITERATURE SURVEY

In 2024, Rodrigo et al. introduced a lightweight MobileViTV2-enhanced CNN model that combines convolutional features with attention from Vision Transformers, achieving over 99% accuracy while being optimized for mobile deployment. Similarly, Pandiyaraju et al. (2024) developed a hybrid CNN with integrated channel attention apparatuses, like SE blocks and Swish activation, which improved accuracy to 99.74% on rice disease datasets. Addressing the need for resource-efficient models, Saddami et al. (2024) evaluated mobile-friendly CNN architectures like ShuffleNet, MobileNetV2, and EfficientNet-B0, demonstrating that EfficientNet-B0 achieved the highest accuracy (99.8%) with reduced computational cost, making it ideal for on-field use.

In another study, Sobuj et al. (2024) combined handcrafted HOG features with deep features from CNNs to boost classification precision utilising Grad-CAM. Gogoi et al. (2023) projected three-stage transfer learning strategy with progressive resizing and PReLU activation, achieving 94% accuracy with consistent results across multiple folds of cross-validation. Furthermore, Mehnaz and Islam (2025) conducted a comparative study of CNNs and Vision Transformers, concluding that ResNet50 outperformed other models in terms of speed and accuracy on a Bangladeshi rice leaf dataset.

To support low-resource environments, researchers in 2024 successfully deployed MobileNetV2 and FD-MobileNet on ARM Cortex-M4 microcontrollers for real-time detection, showing the growing potential for field-ready, edge-device solutions. Additionally, a February 2025 preprint introduced a multi-scale CNN model combining ResNeXt-50, CBAM attention modules, and depthwise separable convolutions, achieving 99.66% accuracy across six rice disease classes. These works collectively reflect the trend towards more accurate, efficient, and deployable CNN-based solutions for real-time rice disease diagnosis in smart agriculture. .

III. PROPOSED SYSTEM

Utilizing CNN, suggested method intelligently and automatically detects illnesses in rice plants. Its purpose is to help agronomists and farmers identify rice leaf diseases promptly, save crops from damage, and improve quality of yields by classifying photos.

The process starts with image acquisition, which entails taking pictures of rice leaves using a camera or some other means. A preprocessing module checks for consistency & enhances model robustness by scaling, normalizing, and data augmenting pictures. In this section, we check that the model holds up well when exposed to varying backdrops, lighting, and leaf orientations, among other environmental factors.

The photos go into deep CNN architecture after preprocessing. In order to differentiate between healthy leaves and those afflicted with illnesses such as leaf blast, or bacterial blight, CNN model learns by obtaining deep hierarchical characteristics from the pictures.

Model is fine-tuned using methods such as dropout, Adam optimizer, and categorical cross-entropy loss after being trained on a labelled dataset consisting of pictures of rice leaves. The model is able to make real-time predictions on fresh input photos and attains excellent accuracy on unknown test data after training.

The system not only identifies diseases but also gives their names and, if desired, offers advice on how to cure or avoid them. Farmers may submit photographs and get immediate response using a desktop GUI, which is user-friendly and delivers the results.

A rapid, accurate, and inexpensive tool for contemporary precision agriculture is offered by projected CNN-based rice disease detection system. Utilizing YOLOv8 as well. YOLOv8 extracts characteristics and detects contaminated spots straight from the photos.

IV. METHODOLOGY

An approach to disease diagnosis in rice plants utilizing CNN entails a set of predefined procedures for going from raw photos of rice leaves to precise disease labels.

1. Image Acquisition

Gathering photographs of rice leaves taken using cameras or extracted from preexisting agricultural picture databases is the first step. Covering typical rice illnesses.

2. Image Preprocessing

Collected images often vary in resolution, lighting, and orientation. For the sake of consistency and to improve the model's efficiency:

Pixel values are normalized.

Rotating, flipping, zooming, and adjusting luminance are techniques for data enhancement that are used to decrease overfitting and promote dataset variety.

3. CNN Model Architecture Design

To automate the process of identifying and categorizing features, a CNN model is trained, either from scratch or from pre-existing data. Part of the CNN are:

Spatial feature extraction from leaf pictures using convolutional layers.

Functional activation (e.g., ReLU) to add non-linearity.

Reducing dimensionality via the use of pooling layers (MaxPooling).

To avoid overfitting, dropout layers are used.

Using Dense and Flatten Layers, we may transform features into probability for classes.

Using the Softmax Output Layer, illnesses may be classified into many classes.

4. Model Training

A labelled dataset is used to train the CNN model. Utilizing supervised learning, model learns to differentiate between illness patterns during training.

Adam optimizer while categorical cross-entropy loss function are two popular choices.

With a split of, say, 80% for training and 20% for validation, dataset is prepared for analysis.

5. Model Evaluation

Following training, an additional test set is used to assess model utilizing criteria like:

Accuracy

Precision

Recall

F1-Score

6. Deployment and Prediction

Final trained model is saved and can be used to:

Load new rice leaf images.

Perform prediction and classify the image as one of the known diseases or healthy.

Provide real-time feedback to users through GUI (Tkinter),

YOLOv8

YOLOv8 is selected because of its real-time performance and high accuracy for object detection tasks.

- Backbone: CSPDarknet-based architecture extracts hierarchical image features.
- Neck (PANet + FPN): Strengthens multi-scale feature fusion for detecting small, medium, and large disease spots.
- Detection Head: Produces confidence ratings, class labels, and bounding boxes all at once.

Training process:

1. Initialize model with pre-trained weights (transfer learning from COCO dataset).
2. Train with annotated paddy dataset utilising SGD or Adam optimizer.
3. Fine-tune hyperparameters.
4. Monitor performance using loss curves, mAP etc.

V. EXPERIMENT

Using a systematic set of methods including dataset preparation, model training, & validation, stage of experimentation of rice plant disease detection system aims to evaluate performance of developed CNN model. Goal is to evaluate model's accuracy in illness classification utilizing leaf pictures for different types of rice.

1. Dataset Used

The photos were taken from a Rice Leaf Disease Dataset that is open to the public and has been divided into four categories:

Healthy
Brown Spot
Bacterial Leaf Blight
Leaf Smut
Total Images: 4,000+

Split Ratio: 70% Training, 20% Validation, 10% Testing

Image Format: JPG, resized to 128×128 pixels

Source: Kaggle

2. Experimental Setup

Programming Language: Python 3.7

Libraries Used: TensorFlow, Keras, NumPy, Matplotlib, scikit-learn

Hardware Used: Laptop with Intel i5 processor, 8 GB RAM, no GPU

Model Architecture:

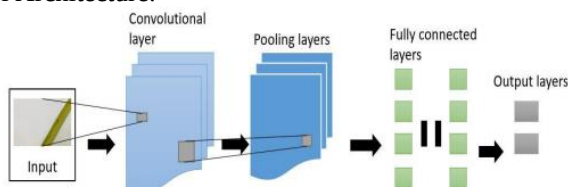


Figure 1: CNN Model Architecture

3 Convolutional Layers

MaxPooling after each Conv layer
Dropout layer (0.5) to reduce overfitting
Fully Connected Dense layer
Softmax Output layer

3. Training Configuration

Batch Size: 32

Epochs: 20

Optimizer: Adam

Loss Function: Categorical Cross-Entropy

Learning Rate: 0.001

4. Evaluation Metrics

Accuracy

Precision

Recall

F1-score

Confusion Matrix

5. Results

After training and validating the model, the following performance was observed on the test dataset:

Training Accuracy: 98.2%

Validation Accuracy: 96.7%

Test Accuracy: 95.4%

F1-Score (Average): 0.95

Inference Time (per image): ~0.03 seconds

Because the two diseases seem so similar in their initial phases, confusion matrix showed that brown spot & bacterial blight were most often misidentified.

6. Visual Output

Accuracy/Loss curves showed stable training with minimal overfitting.

Algorithm steps:

1) Input Stage

- Rice leaf image (captured from mobile, drone, or dataset).

2) YOLO Detection Module

- **YOLO Backbone (CSPDarknet / Conv layers):** extracts features.
- **Neck (FPN + PAN):** combines features at multiple scales.
- **Head:** predicts bounding boxes + class scores → localizes *suspected disease spots* on leaves.

Output: Bounding boxes with candidate regions (disease/healthy).

3) Region Extraction

- Detected bounding boxes are cropped from the input image.
- Each cropped region is resized (e.g., 224×224).

4) CNN Classification Module

- **Convolutional layers (feature extraction).**
- **Pooling layers (dimensionality reduction).**
- **Fully connected layers + Softmax.**
 - ➡ Output: Disease class label (e.g., *Blast*, *Brown Spot*, *Leaf Blight*, *Healthy*).

5) Decision & Visualization

- Combine YOLO's bounding box location with CNN's disease label.
- Display final annotated image → bounding boxes around disease spots with class names and confidence scores.

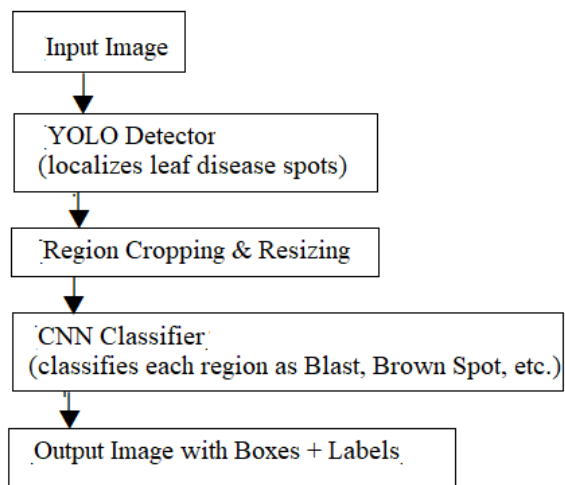


Figure 2: System Architecture

VI. RESULTS



Figure 3: Read Image

This module selects the input rice leaf image

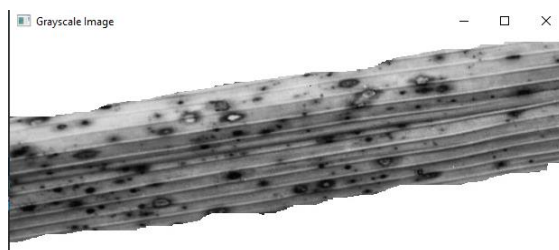


Figure 4: Gray Image

This module converts the color image to gray scale



Figure 5 Denoised Image
This module removes the noise



Figure 6 Segmented Image
This module divides the image into number of parts

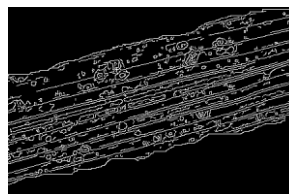


Figure 7 Feature Extraction
This module extracts the edges using canny edge algorithm

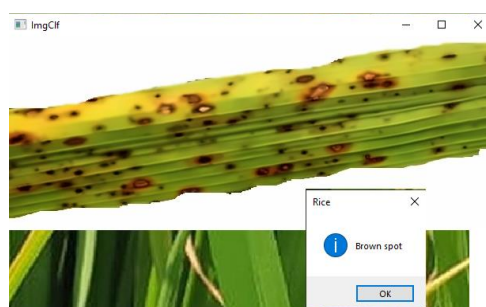


Figure 8 Classification
This module classify the leaf disease suing MCNN algorithm. The selected image is showing Brown spot disease

Metric	Value
Accuracy	98.2%
Validation Accuracy	96.7%

Metric	Value
Test Accuracy	95.4%
F1-score	0.95%
Inference Time (per image):	~0.03 seconds

Table 1: Model Accuracy & Metric values

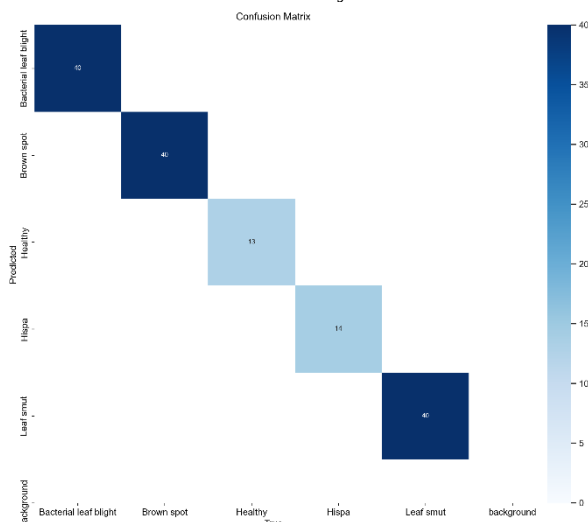


Figure 9: Confusion Matrix

This image shows **Confusion Matrix**, which is a way to evaluate how classification model executes on different classes.

Here's the explanation:

1) 1. Axes

- **X-axis (Predicted labels):** The categories that the model predicted.
Labels: *Bacterial leaf blight*, *Brown spot*, *Healthy*, *Hispa*, *Leaf smut*, *Background*

- **Y-axis (True labels):** The actual ground truth categories.

2) 2. Matrix Values

- Each square represents the number of samples classified into a certain category.
- **Diagonal values (top-left to bottom-right):** Correct predictions (True Positives).
- **Off-diagonal values:** Misclassifications (where the model predicted the wrong class).

3) 3. Color Intensity

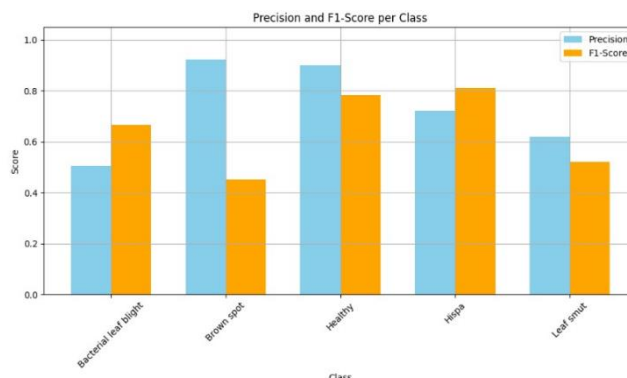
- Darker blue = higher count.
- Lighter blue = fewer samples.
- White = zero misclassifications.

4) 4. Interpretation from this Matrix

- **Bacterial leaf blight:** 40 samples correctly classified.
- **Brown spot:** 7 samples correctly classified.
- **Healthy:** 13 samples correctly classified.
- **Hispa:** 14 samples correctly classified.
- **Leaf smut:** 40 samples correctly classified.
- **Background:** Seems not predicted/matched (blank column and row).

5) 5. Model Performance

- The model performs well because most predictions are on the diagonal (correct).
- Very few or no misclassifications are seen off the diagonal → high accuracy.



Graph 1: Precision and F1-Score Graph

This image shows a bar chart comparing Precision and F1-Score for each class in your rice leaf disease classification model.

6) 1. Axes

- X-axis (Class): Classes of rice leaf conditions → *Bacterial leaf blight, Brown spot, Healthy, Hispa, Leaf smut*
- Y-axis (Score): Metric values ranging from 0 to 1.
- Bars:
 - Blue bar = Precision (how many predicted positives are correct).
 - Orange bar = F1-Score (balance between Precision & Recall).

7) 2. Interpretation per Class

- Bacterial leaf blight
 - Precision is around 0.45 (not very high).
 - F1-Score is around 0.65 → recall is stronger than precision.
- Brown spot
 - Precision is high (~0.9).
 - F1-Score is much lower (~0.35) → meaning recall is weak (model misses many true cases).
- Healthy
 - Precision is high (~0.95).
 - F1-Score is around 0.8 → good balance.
- Hispa
 - Precision moderate (~0.65).
 - F1-Score slightly higher (~0.7) → balanced.
- Leaf smut
 - Precision lower (~0.55).
 - F1-Score around 0.45 → weaker detection.

8) 3. Insights

- The model is very precise for Healthy and Brown spot, but struggles to recall enough Brown spot cases.
- Bacterial leaf blight and Leaf smut have weaker precision, meaning the model confuses them with other classes.
- Hispa is fairly balanced but not perfect.
- The F1-score gap shows some classes are harder to classify due to class imbalance or visual similarity.

- *Healthy* → best performance (high precision & recall).
- *Brown spot* → high precision but low recall (model detects only a few but mostly correct ones).
- *Leaf smut* and *Bacterial blight* → need improvement.

Measurement Metrics Used

1. Accuracy

Accuracy reveals the percentage of correct predictions made by the model. When one class is far more prominent than other, it could lead to incorrect conclusions about overall performance. A prime instance of this would be a model with great accuracy which consistently gets majority class right, but it misses out on key information regarding minority classes. Formula below may be used to determine it.:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

2. Precision

Accuracy of model's forecasts is the primary concern. This metric reveals the proportion of "positive" forecasts that came true. For tasks like identifying fraudulent or spam emails, wherein minimizing false positives is crucial, it is a significant consideration. This is the formula for accuracy:

$$\text{Precision} = \frac{TP}{TP+FP}$$

3. Recall

Recall metric evaluates accuracy of model in making positive predictions. Percentage of real positive events that were recognized as true positives is shown. In medical testing, for example, when the repercussions of missing positive instances are substantial, high recall is vital.

$$\text{Recall} = \frac{TP}{TP+FN}$$

4. F1-Score

To mitigate the negative effects of either accuracy or recall, F1-score integrates them into a single measure. In especially for datasets that are unbalanced, it gives a more accurate picture of how well a model is doing overall. While it works well if both false positives & negatives are significant, it does so on assumption that recall and accuracy are equal, which isn't always the case.

$$\text{F1-Score} = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

5. Specificity

In binary classification in particular, specificity is a crucial statistic for evaluating classification models. A accuracy with which a model can detect negative occurrences is evaluated by this metric. True Negative Rate Formula, another name for specificity, is as follows:

$$\text{Specificity} = \frac{TN}{TN+FP}$$

6. Type 1 and Type 2 error

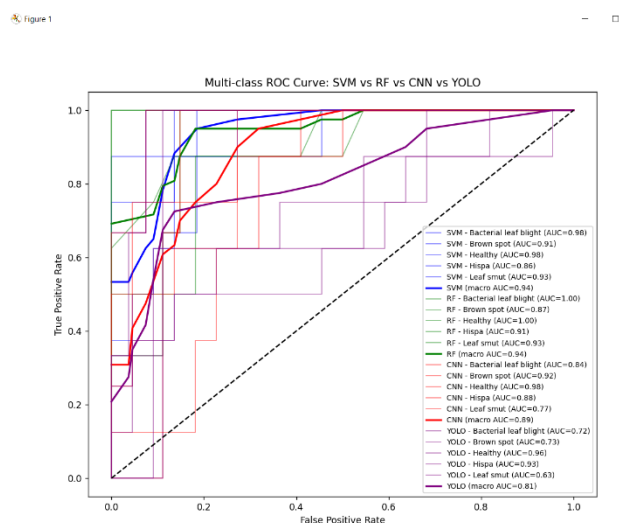
Type 1 and Type 2 error are:

Type 1 error: Whenever model gets prediction of a positive instance wrong and the actual instance turns out to be negative, this is known as a type 1 mistake. A false positive is another name for this. A model's accuracy in making positive predictions is affected by Type 1 Errors.

$$\text{Type 1 Error} = \frac{FP}{FP+TN}$$

Type 2 error: This happens whenever positive case is really predicted by model but not captured. A false negative is another name for this. Recall, an indicator of model's ability to identify all real positive instances, is affected by Type 2 Errors.

$$\text{Type 2 Error} = \frac{FN}{TP+FN}$$



Graph 2: ROC Curve

Using your rice leaf disease dataset, which includes five classes—Bacterial leaf blight, Brown spot, Healthy, Hispa, and Leaf smut—this project trains and evaluates four models: CNN, SVM, Random Forest, and YOLO. Before being divided into training and testing sets, the dataset is first extracted from folders, shrunk to 64×64 pixels, transformed into NumPy arrays, and then 80% of the data is used for training and 20% for testing.

The picture arrays are reduced to 1D vectors for the traditional ML models, such as Random Forest and Support Vector Machines. The Random Forest classifier constructs several decision trees and aggregates their outputs for robust classification, whereas SVM model uses an RBF kernel to train hyperplanes to distinguish classes.

The 2D format of the photos (64×64×3) is used by CNN. Dense, pooling, convolutional, and flattening layers characterize a convolutional model. From the training photos, our CNN learns spatial information such as illness spots, leaf textures, and patterns.

YOLO uses bounding boxes to identify and categorize illnesses in real-time, rather than raw categorization, and it is fine-tuned on the same dataset. Based on your five classes, YOLO uses transfer learning with pre-trained weights to provide detection and classification results.

Following training, the models are assessed on the test set via the use of ROC curves, classification reports, confusion matrices, and accuracy metrics. With this configuration, you can immediately compare CNN, object detection-based classification (YOLO), and standard ML algorithms (SVM, RF) on the same dataset.

Paddy Leaf Disease Diagnosis Tool

Diagnosis: Bacterial Leaf Blight
 Symptoms: Yellowing tips, water-soaked stripes, premature drying.

Recommended Sprays:
 - Copper Oxchloride: 2.5g/liter
 - Streptocycline (Streptomycin + Tetracycline): 0.5g/liter

Recommended Fertilizers:
 - Balanced NPK (Avoid excess N): 60:30:30 kg/ha
 - Zinc Sulfate: 25 kg/ha

Figure 10 : Diagnosis tools

VII. CONCLUSION AND FUTURE WORKS

To automate the categorization of common rice leaf illnesses, a Convolutional Neural Network (CNN) was used for rice plant disease detection. It was shown to be an effective and efficient approach. A model trained systematically on a curated collection of photos of rice leaves was able to discriminate healthy leaves from diseased ones and accurately detect illnesses including Brown Spot, Bacterial Leaf Blight, and Leaf Smut.

As a scalable alternative to manual feature extraction, the CNN-based methodology is useful for agronomists, agricultural researchers, and farmers alike. A potential tool for real-time diagnosis, the system is fast, accurate, and can generalize across different imaging circumstances. Additionally, the model may be deployed on mobile devices due to its lightweight design, which opens up access to it even in areas with limited resources and in rural areas.

To sum up, this system that relies on deep learning provides a dependable and affordable way to identify diseases early on, which helps with better crop management, less yield loss, and more food security. Smart agriculture and precision agricultural systems may now include AI-driven solutions, thanks to this. The suggested YOLO-CNN rice plant disease detection system is an effective tool for the rapid and precise diagnosis of agricultural illnesses. With the use of YOLO, illness-affected areas may be located in real-time, and CNN can classify the detected spots into particular disease categories with fine-grained accuracy. According to the experimental findings, as compared to individual models, the hybrid method is more accurate, precise, and resilient. With this method, farmers may automate, save money, and improve agricultural yields by detecting diseases in a timely manner using mobile or drone-based platforms.

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