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Classification of paddy leaf diseases using an edge-enhanced resnet-50 framework

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Abstract

Timely recognition of paddy leaf diseases is essential for reducing crop losses and supporting field-level disease management. This study evaluated an image-based framework that combines background masking, Canny edge detection, and a ResNet-50 convolutional neural network to classify healthy paddy leaves and leaves affected by bacterial blight, blast, brown spot, and sheath rot. A total of 650 field-acquired images were resized to 300 x 450 pixels, transformed from RGB to HSV color space, and processed using the saturation channel to suppress the background. Color and gray-level co-occurrence matrix descriptors were also computed to characterize lesion regions. The dataset was divided into 455 training images, 65 validation images, and 130 test images. On the test set, the proposed model correctly classified 127 of 130 images, yielding an accuracy of 97.69%, macro-averaged precision of 97.83%, macro-averaged recall of 97.47%, and macro-averaged F1-score of 97.62%. The corresponding accuracy of the reported DNN-JOA baseline was 93.08%. The proposed framework achieved class-wise F1-scores of 98.36% for blast, 98.25% for bacterial blight, 98.11% for brown spot, 95.83% for sheath rot, and 97.56% for healthy leaves. These results demonstrate strong potential for automated paddy leaf disease classification. However, external validation and a controlled ResNet-50 ablation are required before the contribution of canny preprocessing and the model's field generalizability can be established conclusively.

Keywords: Paddy leaf disease; rice; deep learning; ResNet-50; canny edge detection; image classification; GLCM

Introduction

Rice is a staple crop across Asia and a major source of dietary energy and farm income. Its production is constrained by multiple biotic and abiotic stresses, and foliar diseases remain especially important because they directly reduce photosynthetic area and may spread rapidly under favorable field conditions (Mahlein, 2016; Patrício and Inácio, 2018; Vo-Tong Xuan, 2018) [21, 25, 37]. Bacterial blight, blast, brown spot, and sheath rot are among the common paddy diseases that produce visible symptoms on leaf blades and sheaths.

Field diagnosis is traditionally based on visual inspection by farmers or plant-pathology specialists. This approach is practical but can be inconsistent when symptoms are subtle, when multiple diseases share similar colors or lesion shapes, or when field lighting and background conditions vary. Automated image analysis can support diagnosis by quantifying lesion color, texture, and boundary structure (Barbedo *et al.*, 2016; Prajapati *et al.*, 2017) [3, 28].

Classical computer-vision pipelines generally rely on segmentation followed by handcrafted color, texture, and shape descriptors. Deep convolutional neural networks can instead learn hierarchical visual representations directly from images, and residual networks are particularly effective because skip connections support the optimization of deeper architectures (He *et al.*, 2016). Edge information may complement learned features by emphasizing lesion contours and transitions between healthy and affected tissue. Canny edge detection provides a systematic procedure for smoothing, gradient estimation, non-maximum suppression, and edge linking (Canny, 1986) [7]. The objective of this study was to assess an edge-enhanced ResNet-50 workflow for five-class paddy leaf classification. The main contributions are: (i) a preprocessing sequence combining HSV-based background removal and canny edge

extraction; (ii) evaluation on a field-acquired dataset containing four disease classes and healthy leaves; and (iii) class-wise assessment using precision, recall, and F1-score in addition to overall accuracy. The proposed model was also compared descriptively with a previously reported DNN-JOA baseline (Ramesh and Vydeki, 2020)^[30].

2. Related Work

Rice disease recognition has been investigated using both conventional machine-learning and deep-learning techniques. Earlier studies applied support vector machines, k-nearest-neighbor classifiers, radial-basis-function networks, clustering, expert systems, optimization methods, and handcrafted image descriptors to rice and other crop diseases (Pavithra *et al.*, 2015; Pinki *et al.*, 2017; Singh and Misra, 2017; Hassanien *et al.*, 2017; Astonkar and Shandilya, 2018; Kamal *et al.*, 2018; Yusof *et al.*, 2018; Zhang *et al.*, 2018; Krishnakumar and Narayanan, 2019; Pantazi *et al.*, 2019; Ramesh and Vydeki, 2019; Rath and Meher, 2019; Bhatia *et al.*, 2020a, 2020b; Verma *et al.*, 2020)^[2, 4, 15, 17, 18, 24, 26, 27, 29, 31, 34, 36, 38, 39]. These approaches can perform well when segmentation and feature engineering are reliable, but their accuracy often depends strongly on imaging conditions and manually selected descriptors. Deep-learning studies have reported high classification performance for rice and several other crops. Ramesh and Vydeki (2020)^[30] combined an optimized deep neural network with the Jaya algorithm, while Sharma *et al.* (2022)^[32] compared multiple transfer-learning architectures for rice disease diagnosis. Lu *et al.* (2017) used a deep convolutional network for rice disease identification, and Shrivastava and Pradhan (2021)^[33] evaluated color features within a machine-learning framework. Large multi-crop studies using AlexNet, GoogLeNet, VGG, EfficientNet, residual networks, and other convolutional architectures have further demonstrated the capacity of deep models to learn disease-related features (Mohanty *et al.*, 2016; Sladojevic *et al.*, 2016; Amara *et al.*, 2017; Brahimi *et al.*, 2017; Cruz *et al.*, 2017; DeChant *et al.*, 2017; Fuentes *et al.*, 2017; Oppenheim and Shani, 2017; Ferentinos, 2018; Liu *et al.*, 2018; Chowdhury *et al.*, 2021; Dai *et al.*, 2024)^[1, 6, 8, 9, 10, 11, 12, 13, 19, 22, 23, 35]. Reported accuracies across studies are not directly comparable because datasets differ in crop species, class definitions, image counts, background complexity, field conditions, and validation design. Controlled comparisons on the same split and under the same training protocol are therefore preferable to comparisons based only on published headline accuracy.

Table 1: Representative studies on image-based plant disease classification

Study	Crop / dataset	Method	Reported performance
Ramesh and Vydeki (2020) ^[30]	Paddy; own dataset	DNN with Jaya optimization	97% accuracy
Sharma <i>et al.</i> (2022) ^[32]	Rice; own dataset	InceptionResNetV2, Xception, ResNet50, MobileNet, InceptionV3	98.9% accuracy
Lu <i>et al.</i> (2017)	Rice; own dataset	AlexNet-inspired CNN	95% accuracy
Shrivastava and Pradhan (2021) ^[33]	Rice; real-field images	SVM using color features	94.65% accuracy
Mohanty <i>et al.</i> (2016) ^[22]	PlantVillage; 14 crops	AlexNet and GoogLeNet	99.35% accuracy
Ferentinos (2018) ^[12]	PlantVillage; multiple crops	AlexNetOWTBn and VGG	99.53% accuracy
Chowdhury <i>et al.</i> (2021) ^[8]	PlantVillage; tomato	EfficientNet-B4/B7	Up to 99.95%
Dai <i>et al.</i> (2024) ^[10]	PlantVillage	DFN-PSAN feature-fusion network	95.27% accuracy
DeChant <i>et al.</i> (2017) ^[11]	Maize; field imagery	CNN pipeline	97% accuracy
Fuentes <i>et al.</i> (2017) ^[13]	Tomato; field images	VGG and ResNet detector	83% reported AP/IoU performance
Liu <i>et al.</i> (2018) ^[19]	Apple; own dataset	AlexNet-based CNN	98% accuracy
Oppenheim and Shani (2017) ^[23]	Potato; own dataset	VGG-based CNN	96% accuracy
Verma <i>et al.</i> (2020) ^[36]	Plant leaves	Capsule network	91.83% accuracy
Bhatia <i>et al.</i> (2020b) ^[5]	Tomato powdery mildew	Hybrid SVM-logistic regression	92.73% accuracy

3. Materials and Methods

3.1 Dataset and Class Distribution

The dataset consisted of 650 paddy leaf images acquired in a farm environment using a high-resolution digital camera. Five classes were represented: blast (170 images), brown spot (150), bacterial blight (125), sheath rot (110), and healthy leaves (95). The class distribution was moderately imbalanced, with blast as the largest class and healthy leaves as the smallest. Representative images are shown in Figure 2.

Table 2: Distribution of the paddy leaf image dataset

Class	Number of images	Percentage of dataset
Blast	170	26.15%
Brown spot	150	23.08%
Bacterial blight	125	19.23%
Sheath rot	110	16.92%
Healthy	95	14.62%
Total	650	100.00%

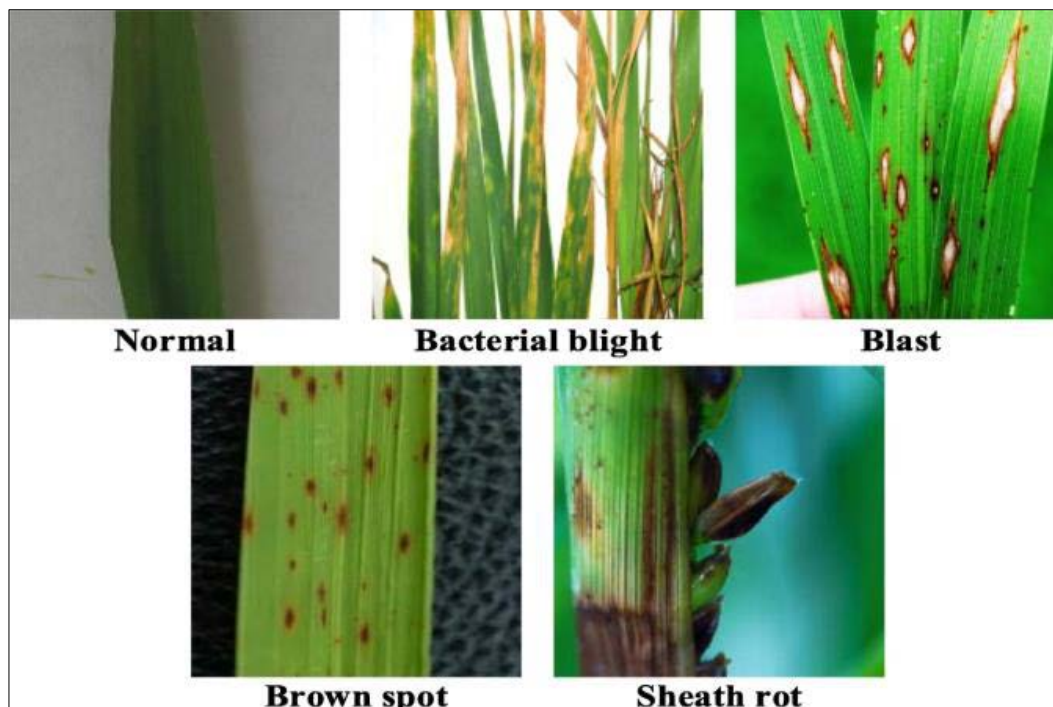


Fig 1: Representative healthy paddy leaves and leaves affected by bacterial blight, blast, brown spot, and sheath rot.

3.2 Image Preprocessing and Background Removal

All images were resized to 300 x 450 pixels. Each RGB image was converted to HSV color space, and the saturation channel was used for foreground-background separation. An empirically selected threshold value of 90 generated a binary mask. The mask was combined with the original RGB image, and background pixels were assigned a value of zero.

Canny edge detection was then applied to the processed image to emphasize lesion boundaries and local intensity transitions. The complete workflow is summarized in Figure 1, while Figures 3 and 4 illustrate the background-removal and edge-extraction stages.

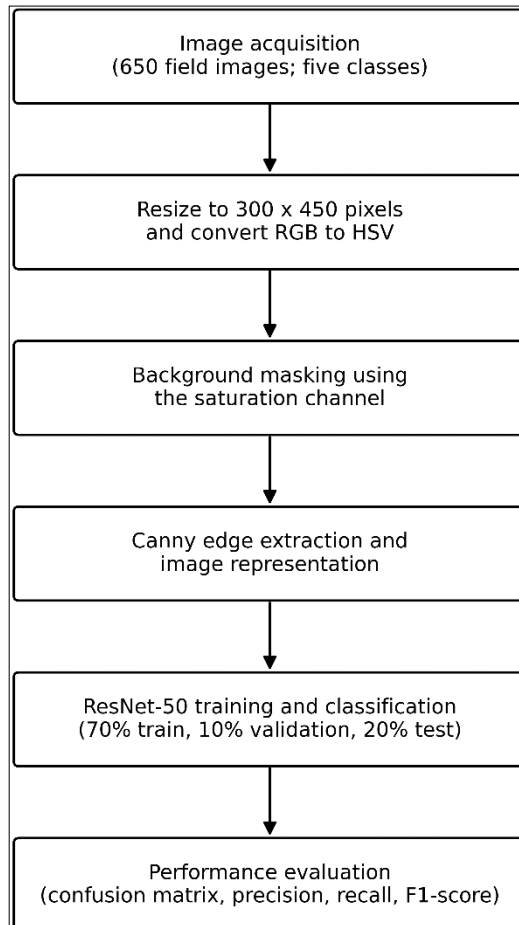


Fig 2: Image acquisition, preprocessing, edge extraction, model training, and evaluation workflow.

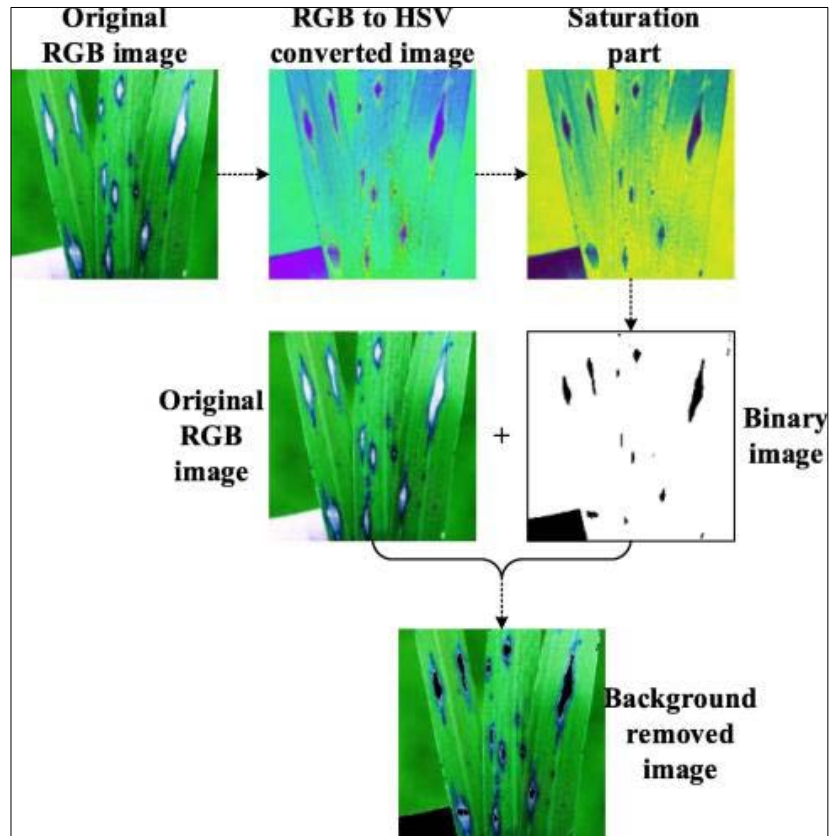


Fig 3: HSV-based background-removal procedure using the saturation channel and a binary mask

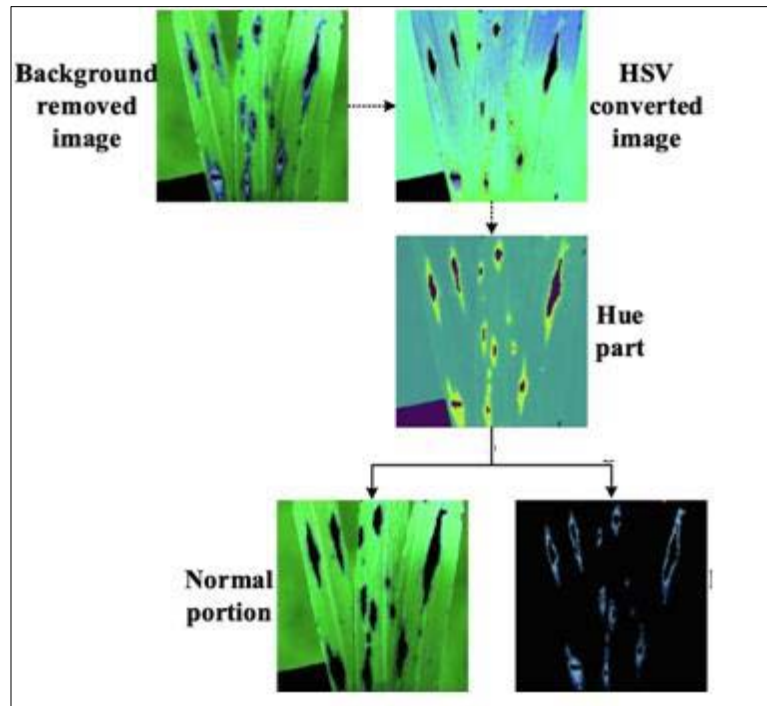


Fig 4: Edge-extraction procedure applied after background removal

3.3 Color and texture characterization

Color and texture descriptors were computed from the disease region to characterize the processed images. For RGB images, the mean and standard deviation of the red, green, and blue Channels were calculated. Mean hue, saturation, and value were obtained in HSV space, and mean L, a, and b values were computed in CIELAB space. For a channel containing N pixels with intensity I_k , the mean and standard deviation were calculated as:

$$\mu = (1/N) \sum_{k=1}^N I_k \quad (1)$$

$$\sigma = \sqrt{(1/N) \sum_{k=1}^N (I_k - \mu)^2} \quad (2)$$

Texture was represented using the gray-level co-occurrence matrix (GLCM), which describes the joint occurrence of gray-level pairs at a specified spatial displacement (Haralick *et al.*, 1973)^[14]. The four descriptors used in the study were homogeneity, contrast, correlation, and energy:

$$\text{Homogeneity} = \sum(i,j) P(i,j) / [1 + (i - j)^2] \quad (3)$$

$$\text{Contrast} = \sum(i,j) (i - j)^2 P(i,j) \quad (4)$$

$$\text{Correlation} = \sum(i,j) [(i - \mu_i)(j - \mu_j) P(i,j)] / (\sigma_i \sigma_j) \quad (5)$$

$$\text{Energy} = \sum(i,j) P(i,j)^2 \quad (6)$$

The extracted descriptors were scaled to the interval [0, 1] using min-max normalization. These descriptors were used to document the visual characteristics of segmented lesions; the deep classifier operated on the processed image representation.

$$x' = (x - x_{\min}) / (x_{\max} - x_{\min}) \quad (7)$$

3.4 Edge-Enhanced ResNet-50 Classifier: ResNet-50 is a residual convolutional neural network composed of an initial convolution and pooling stage followed by four groups of residual blocks. Identity connections allow the input of a residual block to bypass one or more transformations, reducing optimization difficulty in deep networks (He *et al.*, 2016)^[16]. For this study, the network output layer was configured for five classes: blast, bacterial blight, brown spot, sheath rot, and healthy. The edge-enhanced image representation was supplied to the ResNet-50 classification pipeline implemented in MATLAB.

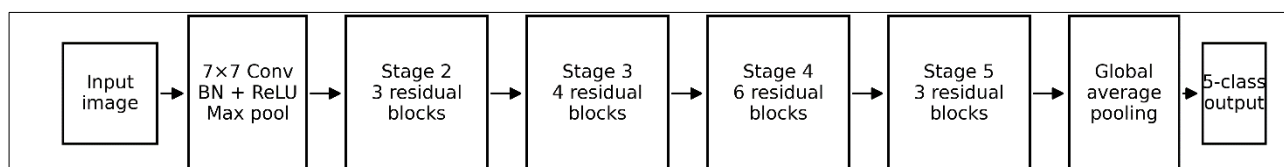


Fig 5: Simplified ResNet-50 architecture used for five-class paddy leaf classification

3.5 Dataset partitioning and evaluation design

The dataset was partitioned into 70% training, 10% validation, and 20% testing subsets, corresponding to 455, 65, and 130 images, respectively. The test set was reserved for final performance estimation. A previously reported DNN-JOA confusion matrix for the same five class labels was used as a descriptive baseline (Ramesh and Vydeki, 2020)^[30]. Because the full training protocol and predictions of the baseline were not available, the comparison was not treated as a controlled significance test.

3.6 Performance Metrics

For each class, true positives (TP), false positives (FP), false negatives (FN), and true negatives (TN) were obtained from the confusion matrix. Precision, recall, F1-score, and overall accuracy were calculated as follows:

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN) \quad (8)$$

$$\text{Precision} = TP / (TP + FP) \quad (9)$$

$$\text{Recall} = TP / (TP + FN) \quad (10)$$

$$\text{F1-score} = 2 \times (\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall}) \quad (11)$$

Macro-averaged metrics were obtained by calculating the unweighted mean across the five classes. Weighted metrics used the number of test samples in each class as weights.

4. Results

4.1 DNN-JOA Baseline

The baseline confusion matrix contained 130 test observations, of which 121 were correctly classified, corresponding to an overall accuracy of 93.08%. The principal errors involved sheath rot, bacterial blight, and brown spot.

Table 3: Confusion matrix for the reported DNN-JOA baseline

Actual / predicted	Blast	Bacterial blight	Brown spot	Sheath rot	Healthy
Blast	29	1	0	0	0
Bacterial blight	1	26	0	0	1
Brown spot	0	0	25	2	0
Sheath rot	1	1	1	22	0
Healthy	0	1	0	0	19

Table 4: Class-wise performance of the DNN-JOA baseline

Class	Precision	Recall	F1-score	Support
Blast	93.55%	96.67%	95.08%	30
Bacterial blight	89.66%	92.86%	91.23%	28
Brown spot	96.15%	92.59%	94.34%	27
Sheath rot	91.67%	88.00%	89.80%	25
Healthy	95.00%	95.00%	95.00%	20
Macro average	93.20%	93.02%	93.09%	130
Weighted average	93.11%	93.08%	93.07%	130

4.2 Proposed Canny + ResNet-50 Model

The proposed model correctly classified 127 of 130 test images. Three errors were observed: one brown spot image was predicted as sheath rot, one sheath rot image was predicted as blast, and one healthy image was predicted as bacterial blight. The resulting overall accuracy was 97.69%.

Table 5: Confusion matrix for the proposed Canny + ResNet-50 model

Actual / predicted	Blast	Bacterial blight	Brown spot	Sheath rot	Healthy
Blast	30	0	0	0	0
Bacterial blight	0	28	0	0	0
Brown spot	0	0	26	1	0
Sheath rot	1	0	0	23	0
Healthy	0	1	0	0	20

Table 6: Class-wise performance of the proposed Canny + ResNet-50 model

Class	Precision	Recall	F1-score	Support
Blast	96.77%	100.00%	98.36%	30
Bacterial blight	96.55%	100.00%	98.25%	28
Brown spot	100.00%	96.30%	98.11%	27
Sheath rot	95.83%	95.83%	95.83%	24
Healthy	100.00%	95.24%	97.56%	21
Macro average	97.83%	97.47%	97.62%	130
Weighted average	97.74%	97.69%	97.69%	130

4.3 Comparative Performance

Relative to the DNN-JOA baseline, the proposed model increased overall accuracy by 4.62 percentage points. Macro F1-score increased from 93.09% to 97.62%. The largest class-wise F1 improvement occurred for bacterial blight, followed by sheath rot. Because the baseline predictions were not available for the same individual samples, no paired significance test was performed.

Table 7: Overall performance comparison between the baseline and proposed models

Metric	DNN-JOA baseline	Canny + ResNet-50	Absolute difference
Accuracy	93.08%	97.69%	+4.62 percentage points
Macro precision	93.20%	97.83%	+4.63 percentage points
Macro recall	93.02%	97.47%	+4.45 percentage points
Macro F1-score	93.09%	97.62%	+4.53 percentage points
Weighted F1-score	93.07%	97.69%	+4.62 percentage points

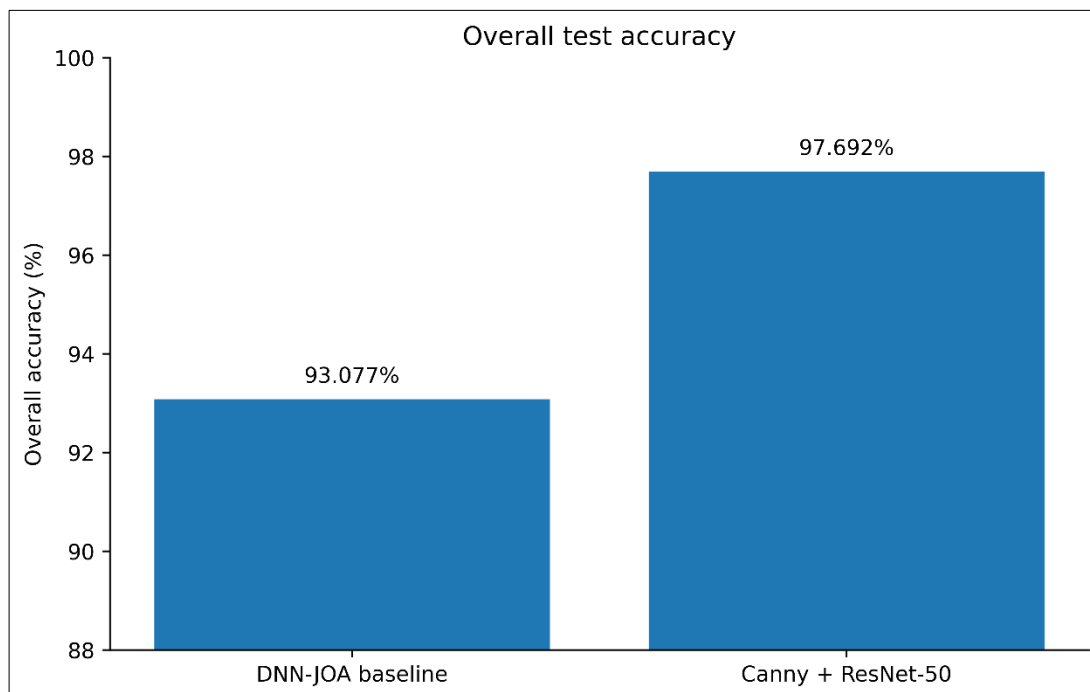


Fig 6: Comparison of overall test accuracy for the DNN-JOA baseline and proposed model.

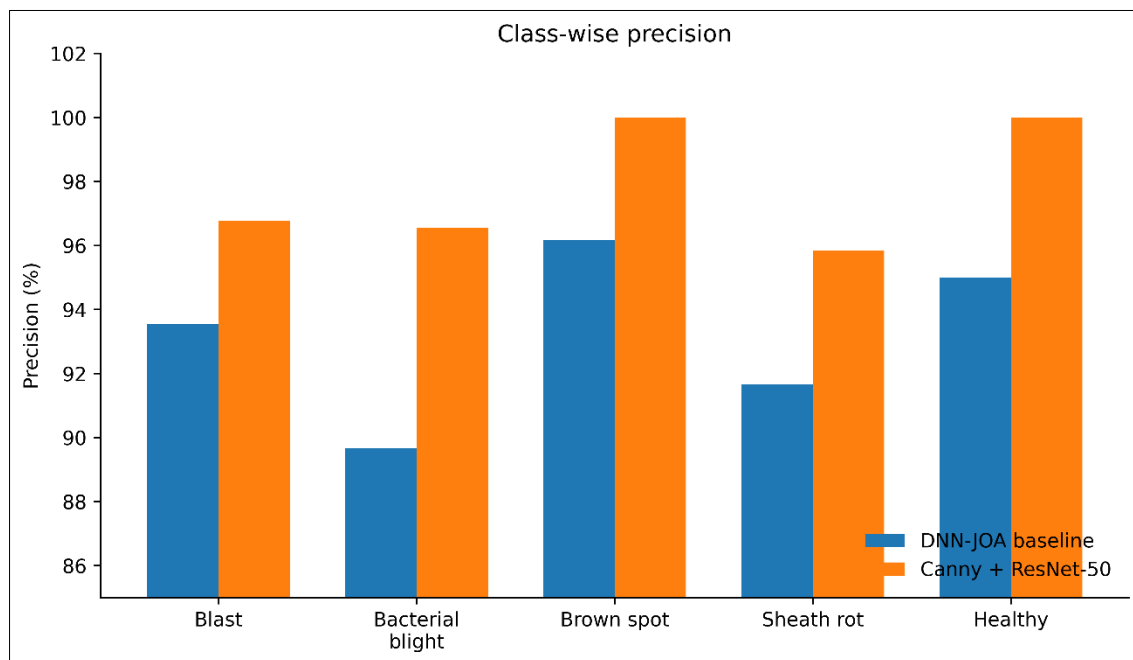


Fig 7: Class-wise precision of the DNN-JOA baseline and proposed model

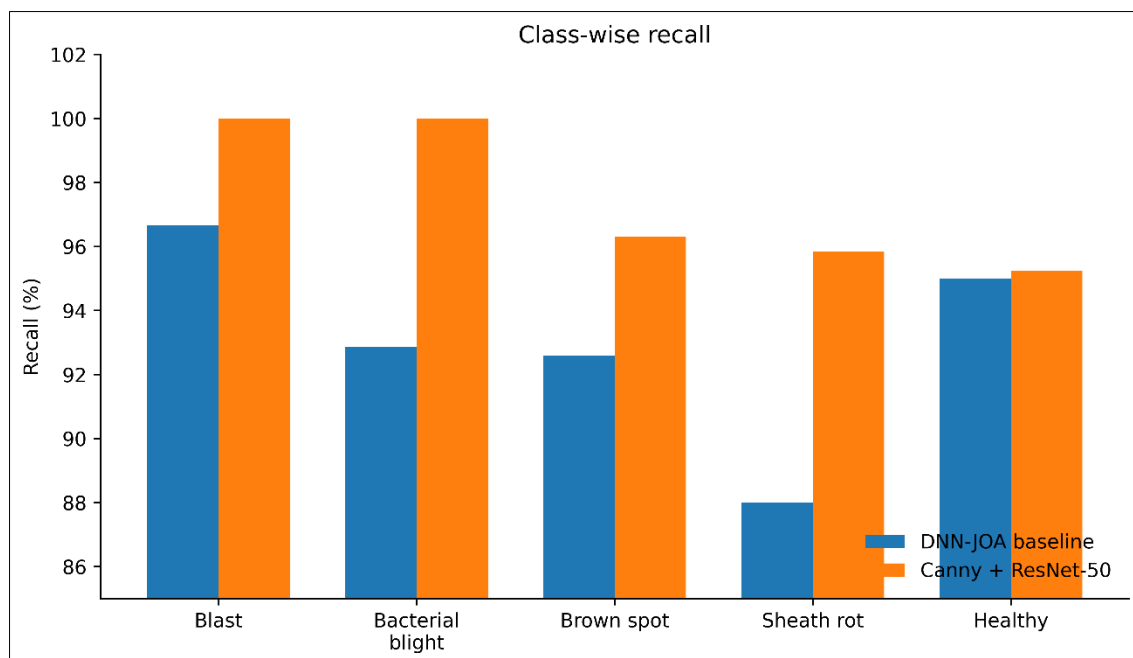


Fig 8: Class-wise recall of the DNN-JOA baseline and proposed model

5. Discussion

The proposed edge-enhanced ResNet-50 framework achieved high test performance across all five paddy leaf categories. The overall accuracy of 97.69% and macro F1-score of 97.62% indicate that the model maintained strong performance despite unequal class frequencies. Precision was highest for brown spot and healthy leaves, while recall was perfect for blast and bacterial blight. Sheath rot remained the most difficult category, although its F1-score was still 95.83%.

The observed error pattern is biologically and visually plausible. Brown spot and sheath rot can both present brown necrotic regions, while sheath rot and blast may share elongated or irregular lesion boundaries. A healthy image predicted as bacterial blight may reflect background artifacts, illumination variation, or early symptoms not visible at the selected resolution. Edge-based preprocessing may help preserve lesion contours, but it can also amplify non-disease edges such as leaf veins, shadows, and image boundaries.

The performance is consistent with rice-specific studies using deep convolutional and transfer-learning architectures (Lu *et al.*, 2017; Shrivastava and Pradhan, 2021; Sharma *et al.*, 2022) [32, 33] and with broader crop-disease studies reporting high classification performance (Mohanty *et al.*, 2016; Sladojevic *et al.*, 2016; Amara *et al.*, 2017; Brahimi *et al.*, 2017; Cruz *et al.*, 2017; DeChant *et al.*, 2017; Fuentes *et al.*, 2017; Oppenheim and Shani, 2017; Ferentinos, 2018; Liu *et al.*, 2018; Chowdhury *et al.*, 2021; Dai *et al.*, 2024) [1, 6, 8, 9, 10, 11, 12, 13, 19, 22, 23, 35]. Nevertheless, published percentages should be interpreted in the context of each dataset. Laboratory images with uniform backgrounds are generally easier than field images, and random image-level splitting can overestimate performance if near-duplicate images from the same plant or acquisition sequence appear in multiple subsets.

The comparison with DNN-JOA suggests an improvement, but the contribution of Canny edge detection cannot be isolated from the change in classifier architecture. A controlled ablation should compare the same ResNet-50 training protocol with and without Canny preprocessing. Such an experiment would show whether edge enhancement provides a reproducible benefit beyond the residual network itself.

Several limitations should be considered. The dataset was relatively small and originated from a single field-acquisition setting. The available experimental record did not include cultivar, season, growth stage, camera model, illumination range, optimizer, learning rate, batch size, epoch count, data augmentation, random seed, or early-stopping criterion. Performance was estimated from one train-validation-test split, without cross-validation or an independent external dataset. In addition, computational time and storage reductions were not measured quantitatively. These limitations restrict reproducibility and prevent strong claims about deployment readiness.

Future work should use larger multi-location datasets, plant- or plot-level splitting, repeated training runs, and an external test set. The model should be evaluated under variable lighting, occlusion, leaf orientation, symptom severity, and mixed infections. Reporting calibration, confidence intervals, class-wise receiver operating characteristics, inference time, model size, and failure-case visualizations would further strengthen practical evaluation. Lightweight architectures should also be considered for mobile or edge-device deployment.

6. Conclusion

This study presented an edge-enhanced ResNet-50 framework for classifying healthy paddy leaves and four important leaf diseases: bacterial blight, blast, brown spot, and sheath rot. The workflow combined HSV-based background removal, Canny edge extraction, and residual convolutional classification. On a 130-image test set, the model achieved 97.69% accuracy and a macro F1-score of 97.62%, outperforming the reported DNN-JOA baseline in the available comparison. The results support the potential of deep residual learning for automated paddy disease screening. However, the model should be regarded as a promising experimental classifier rather than a field-ready diagnostic system until it has been validated using controlled ablation, repeated experiments, and independent multi-location data.

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