

A hybrid deep learning based approach for rice leaf disease detection

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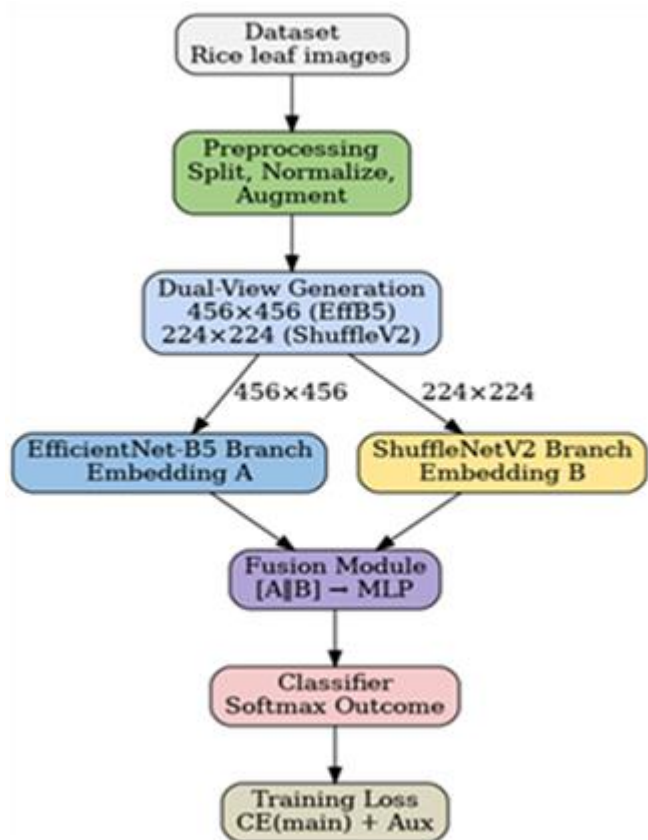
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1 Introduction

Plant diseases cause significant yield losses (~\$220 billion annually) and compromise global food security. Rice, a staple crop, is vulnerable to diseases like bacterial leaf blight and brown spot, which can reduce yields by 30-80%. Traditional diagnosis methods are labor-intensive, subjective, and limited in scalability. Recent advances in computer vision and deep learning enable automated disease classification, but challenges persist in distinguishing similar diseases and providing interpretable outputs. Our proposed hybrid framework integrates deep feature extractors with attention-based feature fusion and ensemble classification to achieve high accuracy, robustness, and interpretability, supporting reliable decision-making in precision agriculture [1]. To address these challenges, we propose a hybrid framework that integrates powerful deep feature extractors with attention-based feature fusion and an ensemble classifier. The objective is to achieve high accuracy while enhancing robustness and interpretability, thereby enabling reliable and scalable decision-making in precision agriculture.

2 Methodology

We propose a hybrid deep learning framework named DeepRL-DetNet. It integrates Convolutional Block Attention Modules (CBAM) with EfficientNet-B5 and ShuffleNetV2 backbones for enhanced feature extraction. Extracted features are fused and optimized through Principal Component Analysis (PCA), followed by classification. The workflow diagram is illustrated in Fig. 1(a), providing a structured overview of the steps involved from data collection to model deployment.



2.1 Architecture of the hybrid model

We propose DeepRL-DetNet, a hybrid framework for rice-leaf disease detection, combining EfficientNet-B5 and ShuffleNetV2 with dual-scale inputs (456x456 and 224x224). The model leverages MBConv blocks and efficient channel operations for feature extraction, and a fusion module for robust classification. Trained with a composite objective, DeepRL-DetNet achieves strong performance, generalization, and real-time deployability for precision agriculture. Fig. 1(b) represents the block diagram of the proposed approach.

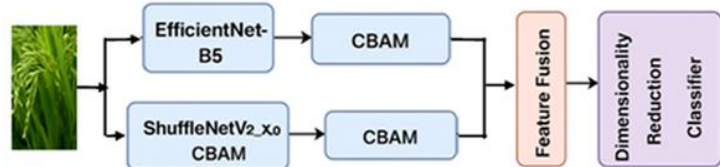


Fig. 1(a). DeepRL-DetNet workflow diagram . Fig. 1(b). DeepRL-DetNet block diagram.

2.2 Working principle of the hybrid model

Our hybrid architecture combines EfficientNet-B5 and ShuffleNetV2 for rice-leaf disease detection, balancing accuracy and efficiency. Dual-scale inputs (456x456 and 224x224) capture fine-grained and coarse features. Data augmentation enhances generalization. The model leverages complementary feature extractors, with EfficientNet-B5 refining deep features and ShuffleNetV2 improving information flow. A fusion module integrates cues, and multi-faceted supervision stabilizes training. The model achieves a strong accuracy-efficiency trade-off, suitable for real-time precision agriculture deployment.

3 Results and Analysis

In this section, summary of performance analysis and benchmarking is presented.

3.1 Overall classification performance

The hybrid model achieves 94% accuracy on the six-class rice-leaf dataset. Class-wise precision/recall/F1 scores remain strong: Bacterial Leaf Blight: 0.91/0.92/0.92, Brown Spot: 0.97/0.94/0.95, Healthy: 0.97/1.00/0.98, Leaf Blast: 0.92/0.89/0.90, Leaf Scald: 0.91/0.95/0.93, Sheath Blight: 0.96/0.94/0.95. Macro and weighted F1 = 0.94, showing balanced performance across all classes. The classification report is presented in Fig. 2.

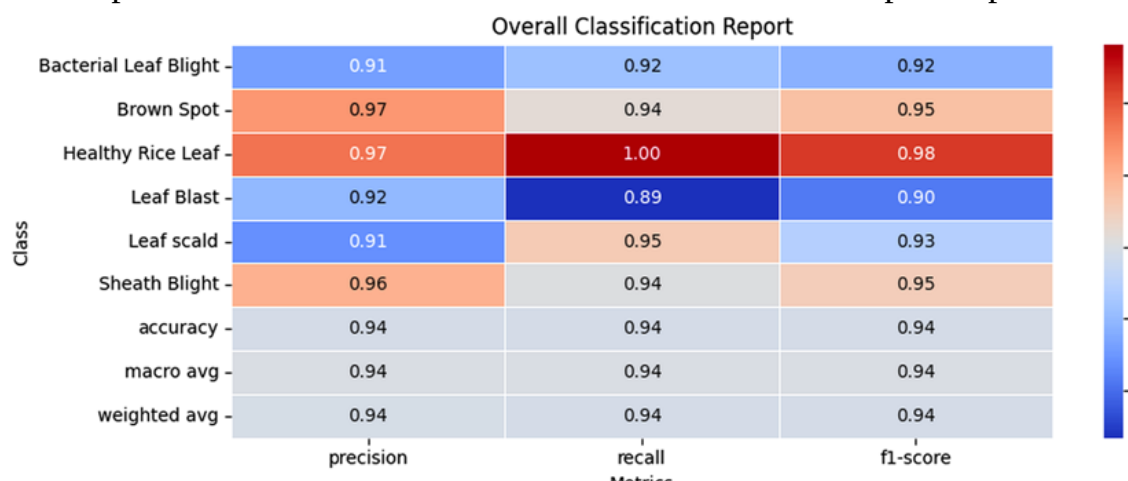


Fig. 2. Classification report.

3.2 Confusion matrix analysis

Most errors occur between Leaf Blast and Bacterial Leaf Blight due to visual similarity. Healthy class is well-separated with 524 true positives and minimal misclassification. The dual-scale design (456x456 & 224x224) enhances lesion boundary detection and context understanding. Future improvements: lesion-aware attention and class-specific augmentation to reduce confusion among similar disease. Fig. 3 represents the confusion matrix.

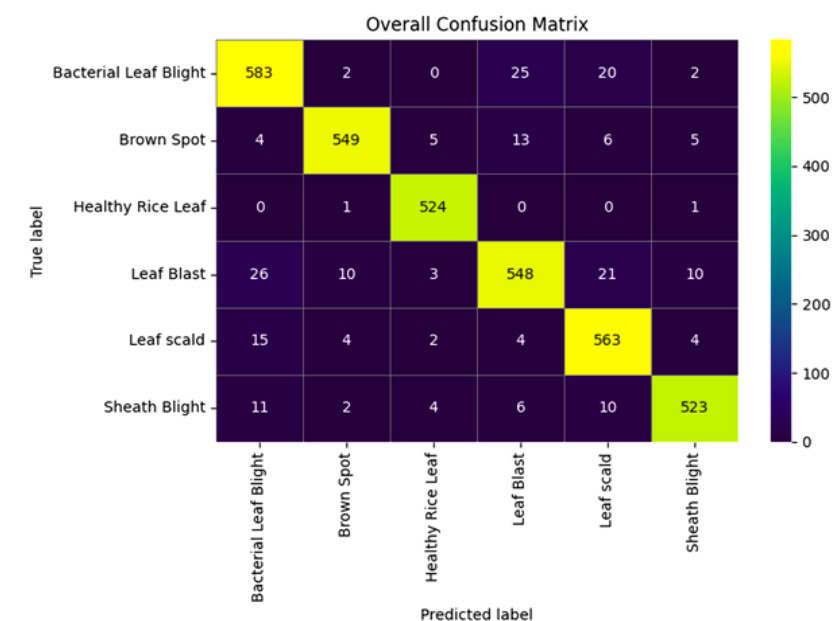


Fig. 3. Confusion matrix.

3.3 ROC–AUC

Fig. 4 represents the ROC curve. Per-class AUCs range 0.98–1.00, with micro-average AUC = 0.99. Healthy and Sheath Blight achieve near-perfect separability; Leaf Blast slightly lower (0.98). These near-ceiling AUCs confirm strong class separability and allow flexible precision–recall tuning.

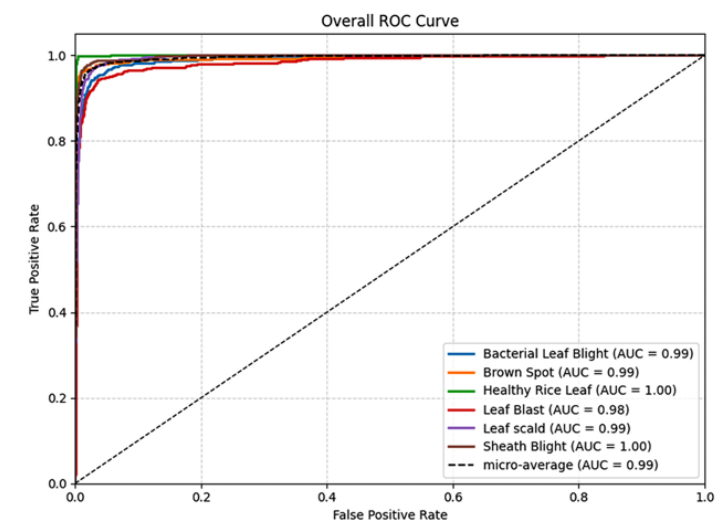


Fig. 4. ROC Curve.

3.4 Benchmark and SOTA comparison

Performance comparison is presented in Table 1. Compared to ResNet-50 (90.8%), DenseNet-121 (91.6%), EfficientNet-B4 (92.1%), EfficientNet-B5 (92.9%), and ShuffleNetV2 (89.7%), the hybrid model achieves 94.0%. It surpasses SSSO-DL (92.6%) [2] and VGG16+InceptionV3 (93.3%) [3]. The hybrid’s combination of EfficientNet-B5 (high capacity) and ShuffleNetV2 (lightweight) provides an optimal accuracy–efficiency trade-off. Overall, it delivers state-of-the-art performance (Accuracy 94%, AUC 0.99) with interpretable results and suitability for field deployment.

Table 1 Performance comparison with benchmark model and SOTA

Method	Proposed by	Accuracy (%)
ResNet50	Benchmark Model	90.8
DenseNet-121		91.6
EfficientNet-B4		92.1
EfficientNet-B5		92.9
ShuffleNetV2		89.7
SSSO-based deep learning	Daniya <i>et al.</i> [2]	92.6
VGG16 and InceptionV3	Rahman <i>et al.</i> [3]	93.3
DeepRL-DetNet	Proposed Model	94.0

4 Conclusion

The proposed DeepRL-DetNet integrates EfficientNet-B5, ShuffleNetV2, CBAM, and PCA-based feature fusion, achieving 94 % accuracy, 0.94 F1, and 0.99 AUC on a six-class rice-leaf dataset. The model offers robust, interpretable performance and real-time potential for precision agriculture. Future work will expand dataset diversity, integrate multimodal data, and optimize mobile/edge deployment.

References

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