

Optimizing Leafnet for Better Rice Leaf Disease Classification

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Abstract: Timely identification of plant diseases is crucial for safeguarding crop yields and ensuring effective disease management. In this research, we perform a comparative study of multiple deep learning models for classifying rice leaf diseases using the Rice Leaf Dataset. The classification phase involves evaluating LeafNet, a Modified LeafNet, MobileNetV2, Xception, NasNetMobile, and an ensemble model combining LeafNet with NasNetMobile. For leaf abnormality detection, we employ object detection architectures from the YOLO family, including YOLOV5x6, YOLOV5s6, YOLOV8n, and YOLOV9n. The primary objective is to enhance accuracy in both disease classification and abnormality detection, thereby supporting precision agriculture practices. Through extensive experimentation, we identify the models that deliver superior performance in their respective tasks. The findings highlight the value of advanced machine learning approaches in modern agriculture, enabling early intervention, efficient disease control, and optimized resource use in rice production.

Index Terms: Deep learning, convolutional neural networks, transfer learning, image classification, Rice Leaf Disease, Classification, Detection, YOLO, LeafNet, Accuracy.

I. Introduction

Agriculture has been central to human civilization, driving food security and urbanization by enabling settled communities through systematic crop cultivation. Today, large-scale farming sustains global food systems, but productivity faces major challenges from crop diseases, causing significant yield losses and economic setbacks.

Alongside pathogens, environmental stressors such as temperature and humidity fluctuations further threaten crop health, especially in tropical and temperate regions. These combined biotic and abiotic stresses raise concerns for sustainable agricultural practices.

Early and accurate disease detection is vital to maintain productivity and food quality. Timely identification enables effective intervention and supports plant ecological research. However, symptoms are often subtle and hard to detect at early stages, posing difficulties for farmers lacking diagnostic tools or expertise.

Rice, a global staple, is highly disease-prone. In 2020–2021, it was cultivated on 163.99 million hectares, yielding 502.10 million metric tons, with a 2.16% decline from previous years due largely to disease. Common rice diseases like brown spot, hispa, and leaf blast remain serious threats. Effective management—through crop rotation, resistant varieties, and timely fungicide use—can mitigate their impact and strengthen resilience.

II. Literature Review

Machine learning (ML) and deep learning (DL) have advanced plant disease detection by enabling accurate and timely diagnosis. Nirmal et al. showed that combining supervised and unsupervised methods improves classification of pomegranate leaf diseases, while Tahir demonstrated the efficiency of Mask R-CNN for real-time detection, adaptable to agricultural monitoring.

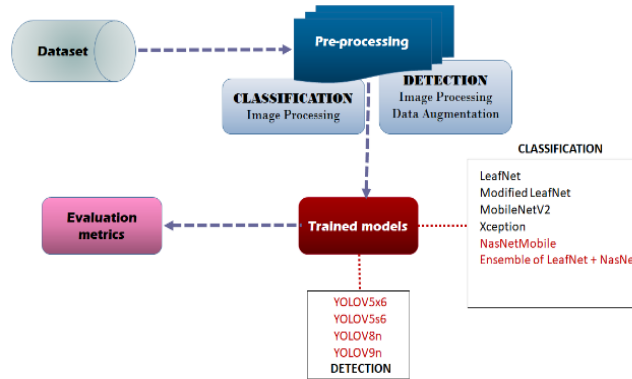
In rice, Elfri et al. used drone imagery with ML to identify crop health issues, highlighting aerial surveillance as an effective tool. Esteva emphasized CNNs, RNNs, and transfer learning in healthcare, approaches equally valuable in agricultural diagnostics. Begoli further stressed uncertainty quantification in AI, essential for reliable disease detection.

Complementary studies explored sustainable management: Chen proved biofungicides effective against rice blast, while Al-Khayri showed nanoparticles improve plant stress tolerance, pointing to integrated detection and treatment strategies. Patil and Kumar advanced this with Rice-fusion, a multimodal DL framework combining RGB, thermal, and spectral data for robust rice disease diagnosis under diverse conditions.

III. Materials And Methods

The proposed system enhances rice leaf disease classification and detection using deep learning and advanced object detection techniques. The Rice Leaf Dataset is processed with classification models—LeafNet, Modified LeafNet, MobileNetV2, Xception, NasNetMobile, and an Ensemble of LeafNet with NasNetMobile—for disease categorization. For abnormality detection, YOLO variants (YOLOv5x6, YOLOv5s6, YOLOv8n, YOLOv9n) are applied to localize infected areas. Transfer learning with CNN architectures improves feature extraction, while a Flask-based web interface provides secure, user-friendly access.

System Workflow:



The dataset undergoes preprocessing and augmentation, followed by classification (using DL models) and detection (using YOLO). Models are evaluated with standard metrics to ensure accuracy.

a) Dataset

The dataset consists of four classes: Brown Spot (418 images), Healthy (1191), Hispa (452), and Leaf Blast (623). For YOLO detection, 1600 images are used for training and 400 for validation.

b) Preprocessing

- **Classification:** Images are rescaled (0–1), reshaped to 128×128 pixels, and augmented with shear and zoom for generalization.
- **Detection:** Images are converted into blobs, annotated, resized, and processed into NumPy arrays. Augmentations such as rotation, scaling, shifting, and flipping increase variability, preventing overfitting.

c) Algorithms

- **Classification Models:**
 - *LeafNet*: Custom CNN for rice disease patterns.
 - *Modified LeafNet*: Improved version with better feature extraction.
 - *MobileNetV2*: Lightweight model for mobile/edge devices.
 - *Xception*: Uses depthwise separable convolutions for high precision.
 - *NasNetMobile*: Architecture search–based, efficient and accurate.
 - *Ensemble (LeafNet + NasNet)*: Combines strengths of both for higher accuracy.
- **Detection Models (YOLO):**
 - *YOLOv5x6*: High accuracy with large input resolution.
 - *YOLOv5s6*: Faster, lightweight variant for real-time use.
 - *YOLOv8n*: Next-gen YOLO with improved speed and precision.
 - *YOLOv9n*: Cutting-edge model offering enhanced detection efficiency.

IV. Experimental Results

The performance of the proposed system was evaluated using standard metrics:

- **Accuracy** – proportion of correct predictions:

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

- **Precision** – fraction of correctly predicted positives:

$$Precision = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$$

- **Recall** – ability to identify all actual positives:

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

- **F1-Score** – harmonic mean of Precision and Recall:

$$F1\ Score = 2 * \frac{Recall \times Precision}{Recall + Precision} * 100$$

- **Mean Average Precision (mAP)** – ranking quality metric

$$mAP = \frac{1}{n} \sum_{k=1}^{k=n} AP_k$$

Table 1 – Performance Evaluation (Classification)

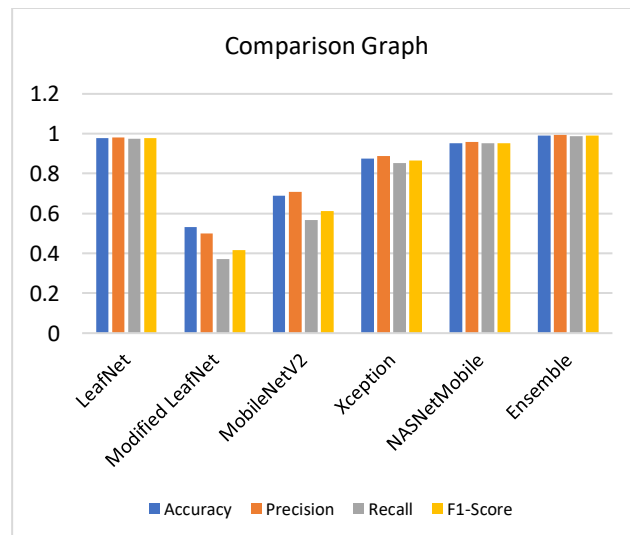
DL Model	Accuracy	Precision	Recall	F1-Score
LeafNet	0.979	0.981	0.976	0.978
Modified LeafNet	0.533	0.501	0.373	0.416
MobileNetV2	0.690	0.707	0.566	0.613
Xception	0.876	0.888	0.853	0.865
NASNetMobile	0.952	0.958	0.951	0.953
Ensemble	0.990	0.993	0.988	0.990

LeafNet+NasNet achieved the best results with **99% accuracy, 99.3% precision, 98.8% recall, and 99% F1-score**, outperforming all other models.

Table 2 – Performance Evaluation (Detection)

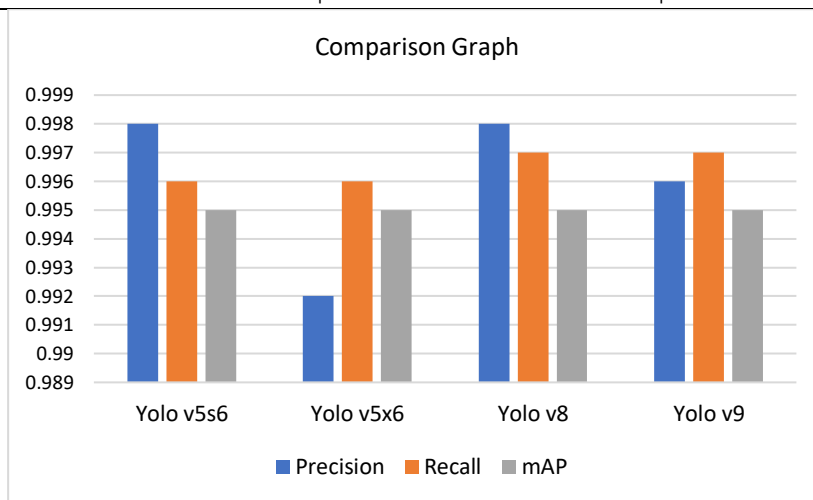
DL Model	Precision	Recall	mAP
Yolo v5s6	0.998	0.996	0.995
Yolo v5x6	0.992	0.996	0.995
Yolo v8	0.998	0.997	0.995
Yolo v9	0.996	0.997	0.995

YOLOv8 obtained the **highest precision (99.8%) and recall (99.7%)**, with superior mAP performance, slightly ahead of other YOLO variants.



Graph 1 – Comparison (Classification)

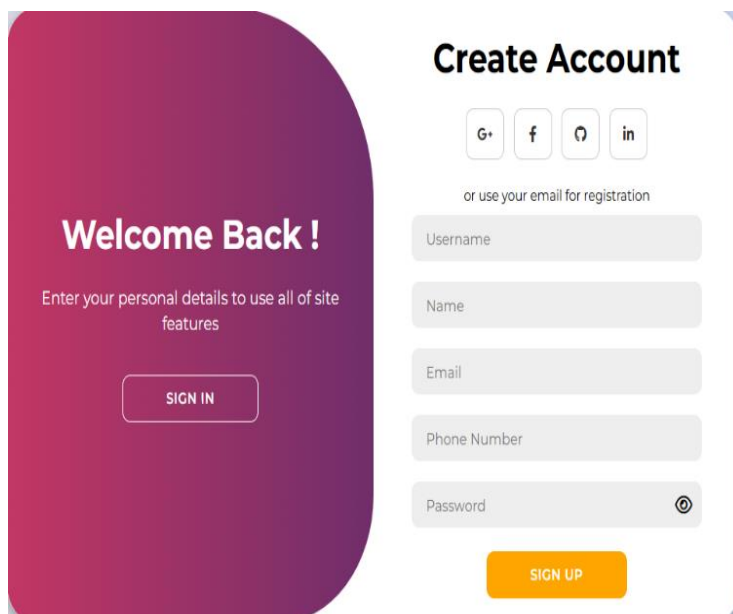
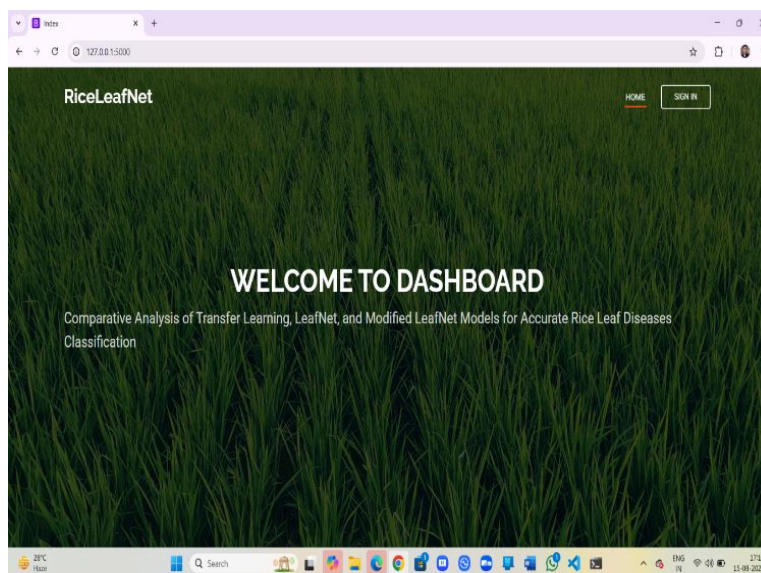
Comparison of models based on Accuracy, Precision, Recall, and F1-score. LeafNet+NasNet leads across all metrics.

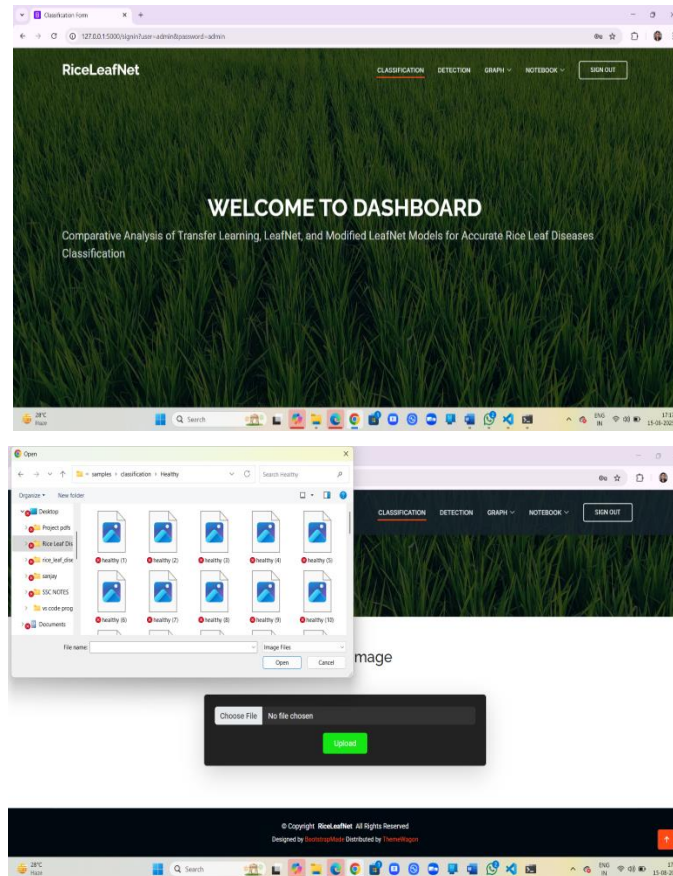
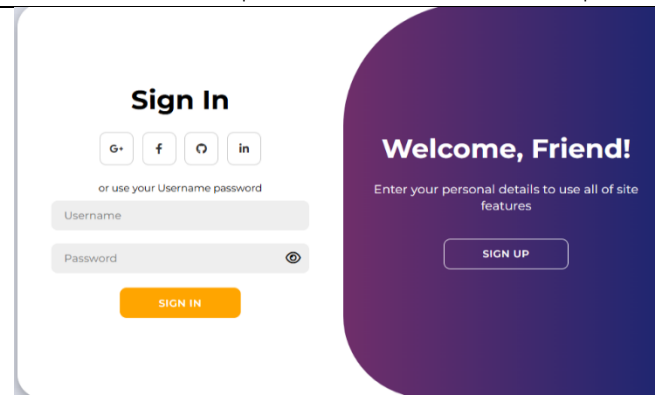


Graph 2 – Comparison (Detection)

Comparison of YOLO variants on Precision, Recall, and mAP. YOLOv8 consistently outperforms others.

Screenshots





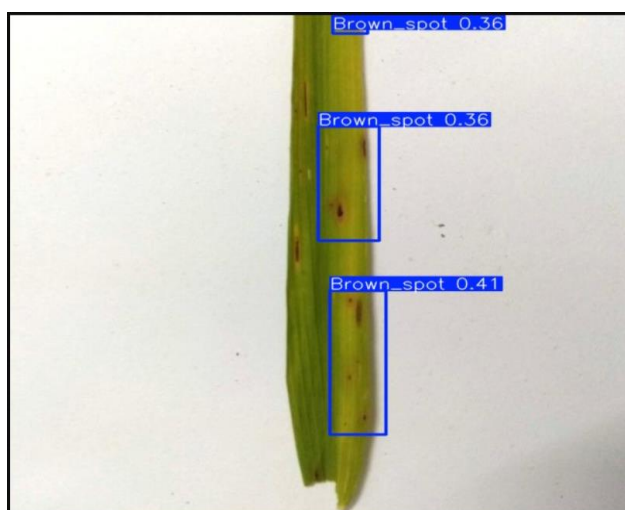
The Prediction is:

Healthy



The Prediction is:

Hispa



V. Conclusion

The proposed system effectively integrates deep learning and object detection for rice leaf disease classification and detection using the Rice Leaf Dataset. Among classification models—LeafNet, Modified LeafNet, MobileNetV2, Xception, NasNetMobile, and their Ensemble—the ensemble achieved the highest accuracy of 99%, confirming the strength of combining custom and transfer learning. For detection, YOLO variants were applied, with **YOLOv8n** achieving the best precision (99.8%) for fine-grained disease localization. The system's Flask-based web interface provides real-time, secure, and user-friendly interaction,

making it suitable for practical agricultural applications. This unified framework supports precision agriculture by enabling timely diagnosis, monitoring, and improved crop health management.

Future Scope: The system can be extended to other crops and diseases using diverse datasets, IoT-enabled drones, and mobile imaging for large-scale monitoring. Enhancements such as multilingual, farmer-friendly interfaces, and advanced models like Vision Transformers with continual learning will further improve accuracy, adaptability, and accessibility for intelligent, automated crop disease management.

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