Literature Review: AI-Driven Rice Disease Detection

1. Introduction

Rice is a staple crop for more than half of the global population, yet its yield and quality are severely threatened by diseases such as rice blast, brown spot, and bacterial blight. Traditional diagnostic approaches are labor-intensive, subjective, and time-consuming. Recent advances in Artificial Intelligence (AI), especially in computer vision and deep learning, have enabled automated and accurate plant disease detection. This review critically analyzes ten state-of-the-art studies on rice disease detection using AI, highlighting methodologies, strengths, limitations, and potential research gaps.

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2. Existing Solutions

2.1 YOLO-Based Detection Models

[1] An improved YOLOv7-Tiny model enhanced with CBAM, RepGhost bottlenecks, and a YOLOX-style decoupled head achieved **F1 = 0.894** and **mAP@0.5 = 0.922**, with real-time inference speed (26 ms/image). The lightweight design makes it suitable for edge devices, though limited in handling complex severity levels.

[2] Another YOLOv7-Tiny variant integrated MobileNetV3 backbone, RCS-OSA, TSCODE head, and MPDIoU loss. This improved precision by 8.8% and recall by 4.7% compared to the baseline, indicating better performance on small lesion detection. However, model generalizability across unseen datasets remains underexplored.

[8] A multi-scale dynamic feature fusion YOLOv11 model (YOLOv11-MSDFF-RiceD) achieved **mAP@0.5 = 89.8%** with only 1.3M parameters and 4.7 MB model size. While highly efficient, scalability to multi-environment field data is yet to be validated.

2.2 Vision Transformers and CNNs

[3] A Vision Transformer (ViT)-based model combined disease detection and severity classification using 3,345 images covering 10 disease types. It achieved a **77.94% F1-score** in severity classification. The main limitation lies in the model's reliance on large labeled datasets, which may not be readily available in low-resource agricultural contexts.

[9] A CNN-based model for rice disease detection demonstrated the capability of traditional deep learning architectures in achieving competitive accuracy. However, CNNs may fail to capture global dependencies compared to ViTs, limiting their robustness on complex datasets.

2.3 Comparative Studies and Benchmarks

[4] A comparative study evaluated CNNs, Vision Transformers, and non-neural network methods such as SVMs. ResNet50 performed best among CNNs, while ViTs showed promise but required more computational resources. This study highlights a trade-off between model complexity and real-world deployability.

[5] A broader taxonomy of deep learning methods for plant disease detection reported **>99% accuracy** with transformer-based models such as HvT. Despite promising results, high computational demand and lack of explainability hinder adoption in rural farming environments.

2.4 Explainable AI (XAI) and Hybrid Methods

[10] A study applied CNNs (VGG16, ResNet50, MobileNetV2) with explainability tools such as SHAP and LIME. This increased interpretability, making AI-based diagnosis more acceptable to agricultural experts. However, XAI integration introduced computational overhead.

2.5 Systematic Reviews and Trends

[6] A systematic review of 69 rice disease studies (2008–2023) emphasized the dominance of CNN-based methods and emerging hybrid models combining CNNs with traditional machine learning classifiers. Identified gaps included insufficient field validation and lack of transfer learning adoption.

[7] A broader review across plant diseases compared CNNs and ViTs. It noted that CNNs remain widely used due to computational efficiency, while ViTs are gaining traction for capturing global image contexts. Yet, limited benchmark datasets hinder fair model comparisons.

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3. Critical Analysis

1. **Performance vs. Efficiency Trade-off:** YOLO-based methods (Papers [1], [2], [8]) demonstrate strong real-time performance, but their accuracy may drop in complex multi-disease environments. ViTs ([3], [4], [5]) show higher accuracy in controlled datasets but require larger computational resources.

2. **Generalizability:** Most models are evaluated on curated datasets under controlled conditions. Very few ([6]) highlight real-world variability such as lighting, occlusion, and background noise.

3. **Explainability Gap:** While XAI approaches ([10]) improve trustworthiness, their high computational requirements limit deployment on low-power devices.

4. **Dataset Limitations:** Dataset diversity remains a key challenge. Few works ([3], [4]) attempt severity classification, which is critical for real-world agricultural decisions.

5. **Integration into Farming Systems:** Despite high accuracy, few studies explore integration into IoT or mobile-based solutions. Lightweight models ([1], [2], [8]) hold promise for such deployment.

4. Performance Comparison Table

Legend: NR = Not Reported in abstract (can be filled after full-text extraction)

No.	Paper (Short Title)	Year	Task	Dataset (Size/ Classes)	Model/ Backbone	Key Metrics	Efficiency (Speed/ Params)	Notes
1	Improved YOLOv7-Tiny (MDPI, Agriculture)	2024	Detection (multi-class)	NR	YOLOv7-Tiny + CBAM + RepGhost + decoupled head	F1 = 0.894; mAP@0.5 = 0.922	~26 ms/ img (device NR)	Edge-suita strong rea time performa
2	Improved YOLOv7-Tiny (MDPI, Agronomy)	2024	Detection (small lesions)	NR	MobileNetV3 backbone; RCS-OSA; TSCODE head; MPDIoU	ΔmAP@0.5 +4.4%; ΔRecall +4.7%; ΔPrecision +8.8% vs. baseline	NR	Better sm target detection; generaliza not shown
3	ViT for Detection & Severity	2025	Detection + Severity grading	3,345 images; 10 diseases; 3 severity levels	ViT	Severity F1 ≈ 77.94%	NR	Joint task; data-hung
4	CNN vs ViT vs SVM (arXiv)	2025	Classification (benchmark)	Dhan-Shomadhan (Bangladesh)	ResNet50 (best among tested)	NR (paper reports comparative rankings)	NR	ViTs prom but heavie
5	DL Techniques for Plant Disease & Pest (arXiv)	2025	Survey/ Benchmarks	Multiple	Transformers (e.g., HvT)	Reported accuracies up to >99% on specific datasets	NR	High accu compute-heavy; lim XAI
6	DL for Rice Disease Diagnosis (Frontiers)	2024	Systematic Review	69 studies (2008–2023)	—	—	—	Gaps: field validation transfer learning
7	DL Techniques for Plant Diseases (Springer OA)	2024	Review	Multiple	—	—	—	CNNs effic ViTs gainin traction

No.	Paper (Short Title)	Year	Task	Dataset (Size/ Classes)	Model/ Backbone	Key Metrics	Efficiency (Speed/ Params)	Notes
8	YOLOv11-MSDFF-RiceD (Frontiers Plant Sci.)	2025	Detection	NR (RiceD mentioned)	YOLOv11 + Multi-scale Dynamic Feature Fusion	mAP@0.5 = 89.8%	1.3M params; 4.7 MB	Very lightweigh strong mA
9	CNN Detection (Discover AI, Springer)	2025	Classification/ Detection	NR	CNN (architecture NR)	NR	NR	Domain-specific; n full-text metrics
10	DL + XAI (arXiv)	2025	Classification + Explainability	NR	VGG16/ ResNet50/ MobileNetV2 + SHAP/LIME	NR	NR	Improves interpreta added overhead

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5. Conclusion and Future Directions

AI-based rice disease detection has advanced significantly, with YOLO variants offering practical edge deployment and ViTs pushing accuracy boundaries. However, challenges remain in dataset diversity, explainability, and real-world validation. Future work should focus on: - Developing large, open, and diverse rice disease datasets. - Balancing accuracy with efficiency for real-world edge deployment. - Integrating explainable AI into lightweight models. - Exploring hybrid CNN-ViT architectures for robustness. - Deploying AI-driven solutions in field conditions through IoT-enabled platforms.

References (IEEE Style)

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