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“IMAGE-BASED RICE LEAF DISEASE DETECTION: A REVIEW OF MACHINE LEARNING AND DEEP LEARNING APPROACHES”

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ABSTRACT

Rice leaf diseases can reduce crop productivity and quality, creating a need for rapid and accessible diagnostic methods. Image-based disease recognition has progressed from hand-crafted colour, texture, shape and lesion descriptors with classical classifiers toward convolutional neural networks (CNNs), transfer learning, lightweight architectures, region-of-interest processing, attention mechanisms, object detection, and hybrid or ensemble models. This narrative review synthesizes representative rice-specific studies across these methodological directions and focuses on what their reported evidence does—and does not—establish. Particular attention is given to dataset provenance, disease-class definitions, image acquisition conditions, splitting procedures, evaluation metrics, model complexity, and evidence of field generalization. Published studies report strong internal performance, but their results arise from different datasets and experimental protocols and therefore should not be interpreted as a common ranking of models. Recent work also shows a growing shift toward lightweight networks and lesion-level detection in natural or field environments. At the same time, differences in image sources, class composition, preprocessing, annotation practices, and validation design continue to limit direct cross-study comparison. The review identifies recurring gaps in dataset diversity, leakage-resistant evaluation, external validation, class-wise reporting, reproducibility, deployment measurement, and interpretability. Based on these observations and established machine-learning reporting principles, a practical reporting and experimental protocol is proposed for future rice disease studies.

Key Words: rice leaf disease detection; rice disease diagnosis; computer vision; machine learning; convolutional neural network; transfer learning; attention; segmentation; object detection; lightweight deep learning; reproducibility; external validation.

I. INTRODUCTION

Rice (*Oryza sativa* L.) is an important food crop, and timely recognition of visible disease symptoms is an important component of crop-health management. Manual diagnosis can be time-consuming and depends on access to experienced personnel. Image-based computer vision provides a non-contact means of analysing visible symptoms and has consequently become an active research direction in agricultural artificial intelligence.

The literature has developed through several methodological stages. Early systems relied on image preprocessing, segmentation and hand-crafted colour, texture or shape features followed by classifiers such as support vector machines (SVMs). Deep CNNs subsequently reduced dependence on manual feature engineering, while transfer learning made pretrained visual representations useful for relatively small agricultural datasets. More recent rice-specific studies have explored attention mechanisms, ROI extraction, lightweight networks, object detection and ensembles. For example, Jiang et al. combined CNN features with SVM classification for four rice diseases and reported 96.8% average

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recognition under their protocol [3]. Rahman et al. evaluated VGG16, InceptionV3 and a smaller CNN on a real-life rice disease and pest dataset and reported 93.3% accuracy for their proposed small CNN [4]. Chen et al. combined a pretrained DenseNet with an Inception module and reported average accuracies above 94% on their public dataset [5]. The subsequent literature shows that high performance is not confined to one architectural family. Wang et al. proposed an attention-based depthwise-separable network with Bayesian optimization and reported 94.65% test accuracy using cross-validated experiments on a four-category rice-disease dataset [6]. Liu et al. combined improved U-Net-based ROI extraction with an attention-enhanced DenseNet and reported 96% accuracy, illustrating the potential value of focusing the classifier on lesion regions [7]. Lightweight work has also become more prominent: an EfficientNet-based attention model reported 95.63% accuracy on a 572-image test set while reducing parameter count relative to EfficientNet-B0 [8].

The evidence therefore supports a more cautious review question than simply asking which architecture has the highest accuracy. The more useful questions are: what data were used; how were labels and splits defined; whether the task was classification or lesion detection; what preprocessing was applied; whether evaluation was internal or external; and what computational evidence supports deployment. This review is organized around those questions.

II. REVIEW SCOPE AND METHOD

This manuscript is a narrative review rather than a systematic review or meta-analysis. The objective was to identify and synthesize representative literature specifically relevant to image-based rice disease identification, with emphasis on classical machine learning, CNN classification, transfer learning, lightweight models, segmentation/ROI processing, attention, object detection, hybrid/ensemble methods, and evaluation reliability.

For the revised manuscript, the literature search was expanded using scholarly web and bibliographic sources including publisher platforms, PubMed, institutional repositories, and indexed academic records. Searches combined rice-specific terms with method terms. Representative queries included: “rice leaf disease detection,” “rice disease classification deep learning,” “rice leaf disease CNN,” “rice disease transfer learning,” “rice leaf disease attention,” “rice disease segmentation U-Net,” “rice disease YOLO,” “lightweight rice disease detection,” and “rice disease field images.” The primary search emphasis was on publications from 2017 through 2026, while older foundational computer-vision and deep-learning papers were retained when they defined an architecture used in the reviewed rice studies.

Studies were included when they addressed image-based identification, classification, localization, or detection of rice diseases and provided sufficient bibliographic information to identify the study and its methodological contribution. Rice-specific primary studies were prioritized for evidence about datasets, architectures, and reported results. Reviews were used to map the field and identify additional primary studies, but review articles were not treated as substitutes for primary experimental evidence. General plant-disease studies were retained only when they directly supported a methodological point, such as dataset bias or transfer-learning behaviour.

Studies were excluded when they were unrelated to image-based rice disease recognition, did not provide identifiable methodological information, or were duplicates of the same experimental work. Where a study reported a performance value, that value was retained only with its dataset/task context. Results were not pooled statistically and were not converted into a cross-paper ranking because disease classes, image sources, split procedures, preprocessing and evaluation protocols differ materially between studies [1], [2], [9].

The search and synthesis were updated for this revision rather than presented as an exhaustive PRISMA systematic review. This distinction is important: the purpose is transparent narrative synthesis, not a claim that every publication in the field has been enumerated.

III. RICE LEAF DISEASE CHARACTERISTICS AND IMAGE-BASED TASKS

Rice disease symptoms vary in colour, geometry, texture, lesion size, distribution and severity. Common image-based categories include bacterial leaf blight, blast, brown spot, sheath blight, tungro and other disease or health categories. The exact class set varies substantially between datasets, which limits direct comparison across studies [1], [2].

Disease/category	Typical visual cues	Image-analysis consideration
Bacterial leaf blight	Elongated pale/yellow/necrotic areas	Symptoms can overlap with other discoloration and vary with disease stage.
Blast	Spindle/elliptical lesions with variable margins	Lesion scale and stage influence recognition.
Brown spot	Brown to dark spots on leaf tissue	Colour and spot size vary with lighting and background.
Sheath blight	Lesions associated with sheath/lower plant regions	Leaf-only datasets may not represent the complete phenotype.
Tungro	Chlorosis/discoloration and growth-related symptoms	Visual similarity with nutrient or other stress symptoms can complicate labels.
Healthy/other categories	Normal or non-disease appearance	Negative-class diversity is important for realistic deployment.

IV. MACHINE LEARNING AND DEEP LEARNING APPROACHES FOR RICE LEAF DISEASE DETECTION

4.1 Classical Machine-Learning Approaches

Conventional image-based disease recognition generally follows image acquisition, preprocessing, segmentation, feature extraction, feature selection and classification. Colour statistics, texture descriptors, shape measurements, lesion geometry and local descriptors can be supplied to SVMs, decision trees, neural networks or Bayesian classifiers. Their main strength is that the representation can be inspected explicitly and the computational pipeline can be relatively compact.

Jiang et al. provide a rice-specific example of a hybrid conventional pipeline in which CNN features were supplied to an SVM, with parameter selection using cross-validation. Their four-disease experiment reported 96.8% average recognition [3]. The methodological significance is not that 96.8% is universally better than other reported values, but that learned features and a conventional classifier can be combined effectively under a defined experimental protocol.

The limitation of hand-crafted or partly hand-crafted systems is sensitivity to image acquisition conditions. Illumination, camera characteristics, cultivar, leaf age, background, disease severity and symptom scale can change the measured features. These limitations help explain the transition toward learned representations, but they also remain relevant because deep networks can learn background correlations if the dataset does not force the model to attend to disease-relevant regions.

4.2. Convolutional Neural Networks

CNNs learn hierarchical representations through convolutional operations and can reduce dependence on manually engineered descriptors. Residual learning in ResNet and multi-scale feature processing in Inception influenced many later plant-disease recognition systems [10], [11].

Rice-specific evidence demonstrates strong performance under controlled or defined test settings. Rahman et al. evaluated VGG16, InceptionV3 and a smaller CNN on 1,426 images covering nine rice disease/pest classes; their proposed small CNN achieved 93.3% accuracy [4]. Chen et al. used a DenseNet/Inception transfer-learning design and reported average predicting accuracy of at least 94.07% in a public dataset, with 98.63% average accuracy for their multiple-disease classification setting [5]. These values should remain attached to the original datasets and protocols rather than being interpreted as architecture-independent estimates.

A broader synthesis suggests that CNN depth alone does not determine practical usefulness. A model may obtain a high score on a small, homogeneous dataset while being expensive to run on a mobile device. Conversely, a compact model may sacrifice some internal accuracy while providing lower memory use and faster inference. Therefore, review of CNN studies should consider data conditions and computational cost together.

4.3 Transfer Learning and Lightweight Architectures

Transfer learning is attractive when rice-disease datasets are smaller than general-purpose image corpora. Chen et al. demonstrated a DenseNet/Inception transfer-learning strategy for rice disease recognition [5], while rice leaf disease work using InceptionResNetV2 reported 95.67% accuracy [12]. The evidence supports transfer learning as a useful initialization strategy, but it does not remove the need for independent validation.

Lightweight architectures address a different problem: deployment under constrained memory and computation. MobileNetV2 uses inverted residual blocks and depthwise convolutions, while EfficientNet uses compound scaling across depth, width and resolution [13], [14]. A rice-specific EfficientNet/attention study reported 95.63% accuracy on a 572-image test set and a 4.4M-parameter model [8]. A lightweight multi-scale CNN study reported 97.1% test accuracy and a 26.1M memory requirement in its own experiment [15].

These results illustrate why deployment claims should include measurable resource information. “Lightweight” should ideally be accompanied by parameter count, model size, computational complexity, memory use, and measured inference latency on the intended device. Accuracy alone cannot establish deployment suitability.

4.4 Segmentation, ROI Processing and Attention

Segmentation and ROI extraction attempt to separate disease-relevant regions from irrelevant background. This is particularly relevant when symptoms occupy only a small fraction of the image. Liu et al. proposed an improved U-Net-based lesion ROI extractor followed by an attention-enhanced DenseNet classifier and reported 96% accuracy for rice leaf disease identification [7]. Sudhesh et al. used Dynamic Mode Decomposition to generate an attention-driven preprocessing/segmentation representation and evaluated ten transfer-learned DCNNs on 3,416 images covering bacterial blight, blast, brown spot and tungro [16].

Attention mechanisms provide a related but learned way of emphasizing informative feature locations or channels. Wang et al. used an attention-based depthwise-separable network with Bayesian optimization and reported 94.65% test accuracy in cross-validated experiments [6]. Yang et al. proposed a residual/attention-enhanced GoogLeNet for rice leaf disease identification, further supporting the use of attention to emphasize disease-relevant features [17]. Lu et al. combined CNN, BiGRU and attention and reported 98.21% accuracy for four rice diseases [18].

Collectively, these studies suggest that lesion-focused processing and attention are promising when symptoms are small or backgrounds are complex. However, they add methodological degrees of freedom. A reproducible paper should therefore report how ROI masks are generated, whether masks require manual annotation, how segmentation errors propagate to classification, what attention module is used, and whether the added component improves performance in an ablation experiment.

4.5 Hybrid, Ensemble and Object-Detection Models

Hybrid approaches combine multiple components, including CNN feature extractors with classical classifiers, attention modules, recurrent layers, multiple pretrained networks, or object detectors. Their motivation is generally to combine complementary representations or to address localization and classification jointly.

RiceNet is an example of a two-stage design: YOLOX first detects diseased regions and the resulting patches are then classified using a Siamese network. The authors reported 95.58% mAP for detection and 99.03% identification accuracy in their experimental setting [19]. This design is relevant to field images because localization can reduce the influence of complex background content.

Recent object-detection studies further shift the task from whole-image classification toward lesion-level localization. YOLO-CRD, for example, was evaluated on naturally acquired rice disease images and reported 90.2% mAP, 90.4% accuracy and 88.0% F1 on its test set, while also reporting computational complexity [20]. A YOLOv5-based improved model has also been proposed for rice leaf disease detection [21]. These studies highlight the importance of distinguishing classification accuracy from detection metrics such as mAP, precision and recall.

Ensemble approaches have also emerged. Uddin et al. developed E2ETCA by fusing InceptionV3, DenseNet-201 and a vision-transformer component and evaluated it across three public datasets and their combined version [22]. The study is important for demonstrating multi-dataset evaluation, but ensemble performance still depends on dataset composition and split design. It should therefore be interpreted as evidence for the investigated framework, not as proof that ensembles universally generalize better.

V. EXPANDED REPRESENTATIVE LITERATURE COMPARISON

Study	Task/data	Approach	Reported result	Critical observation
Jiang et al. (2020) [3]	4 rice diseases	CNN features + SVM	96.8% average recognition	Four-disease task; cross-validation used for SVM parameter selection; result is dataset-specific.
Rahman et al. (2020) [4]	1,426 images; 9 disease/pest classes	VGG16, InceptionV3, small CNN	Small CNN: 93.3% accuracy	Real-life image collection; model-size/deployment considerations were examined.
Chen et al. (2020) [5]	Public rice disease dataset; multiple disease categories	DenseNet + Inception transfer learning	$\geq 94.07\%$ average; 98.63% in multiple-disease setting	Performance is tied to the public dataset and the study's class configuration.
Wang et al. (2021) [6]	Public 4-category rice disease dataset	Attention depthwise-separable NN + Bayesian optimization	94.65% test accuracy	Cross-validated experiments; includes feature visualisation for interpretability.
InceptionResNetV2 study (2021) [12]	Rice leaf disease images	Transfer-learned InceptionResNetV2	95.67% accuracy	Demonstrates transfer learning; direct comparison requires the same dataset/protocol.
Liu et al. (2022) [7]	Rice leaf disease images	Improved U-Net ROI + attention DenseNet	96% accuracy	Shows potential benefit of lesion-focused preprocessing; added pipeline complexity requires documentation.
EfficientNet/attention study (2022) [8]	572-image test set; 5 categories	EfficientNet-B0 + CBAM + Ghost module	95.63% accuracy	4.4M parameters; useful deployment evidence, but small test set.
Multi-scale lightweight CNN (2022) [15]	Rice leaf disease images	Multi-scale CNN based on VGG	97.1% test accuracy	Reports 26.1M memory requirement; accuracy and memory should be interpreted together.
RiceNet (2023) [19]	4 rice diseases; complex-scene images	YOLOX + Siamese network	95.58% detection mAP; 99.03% identification	Two-stage localization/classification; directly addresses complex background.
Sudhesh et al. (2023) [16]	3,416 images; 4 diseases	DMD ROI + 10 transfer-learned DCNNs	93.87% for initial DCNN comparison	Evaluated ROI preprocessing and on-field images; useful for studying preprocessing sensitivity.
Lu et al. (2023) [18]	4 rice diseases	Improved CNN + BiGRU + attention	98.21% accuracy	Hybrid feature-relation model; architectural detail and dataset context are essential.
Uddin et al.	3 public datasets +	InceptionV3 +	Reported multi-	Tests multiple public

(2024/2026 issue) [22]	combined set	DenseNet-201 + ViT ensemble	dataset gains	datasets; demonstrates the value of cross-dataset evaluation.
YOLO-CRD (2024) [20]	Natural-environment rice images; 4 disease types	Lightweight YOLOv5-based detector + attention/Ghost modules	90.2% mAP; 90.4% accuracy; 88.0 F1	Field-oriented detection; reports computational cost and disease-wise AP.
YOLOv5-EFFICIENT (2024) [23]	Rice leaf disease detection dataset	Improved YOLOv5 with CBAM and modified anchors/loss	Detection performance reported in study	Illustrates shift from image classification to multi-scale lesion detection.

The table intentionally does not rank these studies. A 98% classification accuracy on a curated four-class dataset is not directly equivalent to 90% mAP on natural field images, and neither is directly comparable to a nine-class dataset or a two-stage detection task. The appropriate interpretation is methodological: the literature increasingly addresses representation learning, lesion focus, computational efficiency and localization, but evaluation remains heterogeneous.

5.1 Critical Synthesis: What the Literature Collectively Shows

First, deep learning has largely displaced hand-crafted pipelines in the rice-image literature, but the transition has not solved the underlying data problem. Multiple studies report high internal accuracy, yet the class set, image source and evaluation protocol vary. Consequently, architecture changes should not be interpreted independently of dataset design. Second, attention and ROI mechanisms appear repeatedly in studies where disease symptoms occupy limited image area or background information is substantial. The evidence from U-Net/ROI, DMD preprocessing, attention-enhanced CNNs and attention-based lightweight networks is consistent with the hypothesis that disease-focused representation can be useful [6], [7], [16], [17]. However, few studies make the contribution of each component clear through identical-data ablations, and added preprocessing can itself introduce annotation and reproducibility costs.

Third, the literature is moving from classification toward localization and field-oriented detection. RiceNet and more recent YOLO-based studies treat disease regions as objects rather than only assigning a label to the whole image [19]–[23]. This is important for field deployment because a farmer may need to know not only the disease category but also where symptomatic regions occur. Nevertheless, detection performance should be reported using localization metrics and should not be conflated with image-classification accuracy.

Fourth, lightweight architectures are increasingly motivated by deployment. Mobile-compatible attention models, EfficientNet variants and lightweight YOLO systems provide evidence that researchers are considering parameters, memory and inference speed in addition to accuracy [6], [8], [15], [20]. Yet device-level latency, energy use and robustness under changing environmental conditions remain inconsistently reported.

Finally, the literature increasingly recognises generalization as a central issue. Field-oriented datasets contain illumination variation, complex backgrounds, different viewpoints and symptom stages, while public benchmark datasets may be more homogeneous. The difference matters because a model can learn correlations associated with image source rather than disease biology. Barbedo's broader plant-disease analysis likewise showed that dataset size and variety can substantially affect deep-learning effectiveness [9].

5.2 Research Gaps Identified from the Literature

Dataset diversity and provenance. Rice studies use different public, web-sourced, laboratory, and field-collected datasets. Sudhesh et al. explicitly assembled images from web sources, whereas other work collected images in agricultural environments [16]. This variation supports the need to report source, location, acquisition device, disease stage and class distribution.

Evaluation consistency. The reviewed studies use classification accuracy, precision/recall/F1, mAP, cross-validation and different train/test designs. These are not interchangeable outcomes. The heterogeneity visible in the comparison table is itself evidence that cross-paper numerical ranking is inappropriate.

Leakage-resistant splitting. Image datasets can contain near-duplicates, multiple views of the same plant, or augmented versions of the same source image. The literature does not consistently report plant-, field- or collection-session-level grouping. Future work should therefore document the unit of splitting and duplicate screening.

Class imbalance and class-wise performance. Overall accuracy can conceal weak performance in minority categories. Reporting support counts, per-class precision/recall/F1 and confusion matrices is therefore preferable to accuracy alone.

External validation. Several studies evaluate on internal test sets; relatively fewer provide an independently collected test set from a different location, device or acquisition period. Field-oriented work demonstrates the difficulty of natural backgrounds, but independent cross-location validation remains a major need.

Deployment evidence. Lightweight models reduce parameters, but parameter count alone does not establish practical efficiency. Future papers should report measured latency, memory, model size and, where relevant, energy use on the intended hardware.

Interpretability. Attention maps, activation maps and saliency visualisations can show what the network attends to, but visual agreement with lesions is not equivalent to biological validation. Interpretability claims should therefore be treated as explanatory evidence rather than proof of causal correctness.

Reproducibility. Complete descriptions of preprocessing, augmentation, pretrained weights, optimizer settings, random seeds, model architecture and data splits are still necessary for independent replication. Hybrid systems especially require layer-level or fusion-level specifications.

VI. RECOMMENDED EXPERIMENTAL AND REPORTING PROTOCOL

The protocol below is a synthesis of recurring limitations in the reviewed rice literature together with established good practice for machine-learning experimentation. It is not presented as a validated new standard. Its purpose is to translate the review findings into a minimum reproducibility checklist.

Stage	Recommended minimum reporting
Dataset	Source/ownership, access statement, collection location/date, device, disease definitions, total images, per-class counts and field/controlled conditions.
Data cleaning	Corrupt-image handling, label verification, duplicate and near-duplicate screening, and documentation of exclusions.
Splitting	Exact train/validation/test counts; grouping by plant, field, session or original image where related samples exist; no test-set tuning.
Preprocessing	Input size, normalization, colour handling, segmentation/ROI method, augmentation operations and when augmentation is applied.
Model	Architecture diagram, pretrained weights, frozen/trainable layers, classifier head, attention module and exact hybrid/ensemble fusion mechanism.
Training	Optimizer, learning rate, scheduler, batch size, epochs, loss, random seed, early stopping, hardware/software versions.
Evaluation	Accuracy plus class-wise precision, recall, F1, support and confusion matrix; mAP/IoU for detection/segmentation; repeated-run variation where feasible.
Leakage control	Split before augmentation; no cross-split duplicates or near-duplicates; no use of test results for model selection.
External validation	Independent images from different fields, devices, dates, lighting or geographic regions; report results separately from internal test performance.

Deployment	Parameter count, model size, FLOPs/GFLOPs where useful, measured latency/FPS, memory use and target-device specifications.
Reproducibility	Code, configuration, model weights and dataset access where legally permitted; otherwise provide enough detail for reconstruction.

These recommendations are supported by the recurring experimental differences observed across the reviewed studies. In particular, the use of different datasets and evaluation procedures in [3]–[8], [12], [15]–[23] demonstrates why dataset and split information must accompany performance values. The recommendation to separate internal and external validation follows directly from the distinction between benchmark performance and field generalization visible in field-oriented detection studies [19], [20].

VII. LIMITATIONS OF THIS REVIEW

This revised manuscript is a narrative review and does not claim to be a PRISMA-style systematic review or meta-analysis. The search strategy is described to improve transparency, but the included studies remain a focused selection rather than an exhaustive census. Publication bias and differences in indexing may therefore affect the evidence base. Reported performance values are reproduced as published-study results and are not statistically pooled. In addition, some studies provide incomplete information about dataset provenance or split design, so methodological observations are limited to what could be verified from the available records.

VIII. CONCLUSION AND FUTURE SCOPE

Image-based rice leaf disease detection has progressed from hand-crafted features and classical classifiers toward CNNs, transfer learning, lightweight architectures, ROI/segmentation, attention, object detection and ensemble systems. The expanded literature shows that no single methodological family can be declared universally superior because studies solve different tasks on different datasets under different protocols.

The strongest recurring lesson is methodological rather than architectural. High internal accuracy is useful evidence of performance on a defined dataset, but it does not by itself establish robustness to new fields, cultivars, devices, lighting conditions or disease stages. The reviewed work increasingly addresses these issues through lesion-focused processing, lightweight models and field-oriented detection, but independent external validation remains less consistently demonstrated.

Future rice disease studies should therefore report dataset provenance, class definitions, acquisition conditions, leakage-resistant splits, preprocessing, model details, class-wise metrics and computational cost. Classification studies should be distinguished clearly from localization and segmentation studies. Where deployment is claimed, measured device-level performance should accompany model size. Finally, independently collected field images should be treated as a key component of validation rather than an optional extension. These practices would make future results easier to reproduce, compare and translate into reliable agricultural applications.

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