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Review Article

Review of Machine Learning Approaches for Leaf Disease Detection in Rice Crop: Trends, Challenges, and Future Opportunities

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Abstract - *Rice leaf disease is of important concern in developing countries, especially when the livelihood of a major population is dependent on agronomy. Rice is considered a staple crop in South Asian countries, foliar pathogens in rice cause substantial yield loss and economical burden. This review systematically examines the evolution of machine learning and state-of-the-art deep learning approaches for the detection of rice leaf disease. Unlike studies concentrated only on model performance, this review focused on the complete pipeline - spanning challenges observed during image acquisition, preprocessing steps, data characterization, features representation, classification methodology used, along with misused evaluation metrics leading to unsuccessful real-world deployment. This literature reveals a clear paradigm shift from handcrafted feature-based machine learning systems to deep learning architectures, because of their consistently high accuracy, learning discriminative representations directly from raw images without any human intervention. This review also highlights the growing demand for lightweight models for smarter IoT deployments. Overall evidence indicates that the future of automatic rice leaf detection depends on creating standardized benchmark datasets, robust cross-domain validation, and collaborating with smart agriculture frameworks combined with cognitive computer vision and domain adaptive learning, which are capable of accurate disease diagnosis under diverse field conditions.*

Keywords - *Deep learning, Handcrafted features, Leaf disease, Machine learning, Rice crop.*

1. Introduction

Around fifty percent of the world population depends on Rice (*Oryza sativa*) for its caloric needs [1]. Specially in Southeast Asian countries, rice is considered the staple food and accounts for three-quarters of daily caloric intake [2]. Ninety percent of global rice requirement is fulfilled by Asian countries, out of which India and China together contribute about 45% of the total Asian supply [3]. A majority of the population is directly or indirectly related to rice production for livelihood. Thus, the production of rice has a significant economic effect and food security concern in developing countries.

Leaf disease is considered one of the major constraints on rice productivity. Diseases like rice blast and bacterial blight make the leaf dry. On the other hand, sheath blight and brown spot reduce photosynthesis, leading to restricted grain filling, and in severe cases, causing leaf death, resulting in substantial yield losses [4]. As reported [5], rice blast alone may reduce yield by 10-30% and, if not controlled in time, severe outbreaks can wipe out entire fields. Similarly, a 60% production loss was reported by [6] due to bacterial blight. Pre-harvest crop loss accounts for 40% of global crop production, resulting in significant economic costs of about $40 billion annually.

The conventional crop screening is slow, time-consuming, requires expertise, and is labour-intensive [7]. Also, the disease symptoms appear late in the rice leaf, resulting in delayed management. These challenges create a clear need for automated, scalable systems that can detect diseases before severe symptoms develop and reduce unnecessary chemical use. Therefore, early diagnosis offers one of the most effective ways to limit the crop from damage. Timely detection with accuracy optimizes pest and fungicide controls and reduces crop damage, resulting in high yield [8]. Machine learning and deep learning algorithms have gained popularity in plant pathology over the past decade. Traditional models, like support vector machines and the random forests approach, rely on hand-crafted features extracted from leaf images, which are time-consuming and subject to limited feature extraction. On the other hand, Convolutional Neural Networks (CNNs) changed this scenario by learning spatial features directly from raw images. The majority of the studies

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have achieved a high accuracy of 95% and above using CNN algorithms, when trained with enough annotated samples, for rice disease datasets [9]. Transfer learning and attention mechanisms enhance the leveraging of knowledge and ability to extract critical features when training data is limited. As a result, machine learning and deep learning have become necessary tools in crop leaf disease detection. The traditional disease diagnosis involves visual inspection and human intelligence. In large cultivation areas, conventional disease diagnosis is labour-intensive and time-consuming. Human intervention in disease diagnosis increases the risk of errors, specially in the early stage diagnosis or in the case of overlapping disease symptoms. Variation of field conditions, such as light illumination (day light conditions), background clutter, and leave orientation, makes diagnosis difficult. Geographical conditions like location and seasonal variations further complicate the diagnosis process.

Machine learning and deep learning are evolving as a quick and effective alternative to handle the above-mentioned complexities. Many researchers reported model accuracy above 95% using small and unbalanced data sets, evaluated under controlled laboratory conditions. Performance of such a laboratory-trained model severely degrades when subjected to real and diverse field conditions. Therefore, a high model accuracy is not a guarantee that it is ready for real field application. Only Deep learning and machine learning architectural reviews were commonly observed in existing literature. Most of them were found reviewing algorithms or comparing the accuracy values, whereas a quality rice leaf disease diagnosis should include the combined influence of image acquisition technique, process adopted, selection of diverse dataset, class imbalance effect, validation used, model interpretability, computational requirement and most importantly, field deployment capabilities.

Furthermore, while reporting the performance values, an imbalanced dataset, non-equivalent classes and variation in adopted evaluation metrics were frequently observed. Results obtained by considering the above imbalance produce misleading conclusions. Thus, in order to achieve a real field deployment, it is not enough to only report which methods give better performance. However, it also requires to be documented why these improvements occur and weather this improvement sustains with real field deployment. This review addresses recent advances in deep learning and machine learning techniques deployed for detecting rice leaf diseases. It starts by focusing on the significance of the rice crop and how foliar diseases impact crop yield, then extends to imaging, followed by the preprocessing techniques required to build reliable datasets. Three challenges, fist is the limited dataset constraint, then inappropriate model interpretability and finally, deployment issues, where observed during the course of this survey, while comparing the performance of AI and ML architectures for detecting the rice leaf disease. Finally, it outlines future directions for integrated smart farming systems, including explainable AI. The goal of this review is to clarify current trends and point to opportunities for more robust disease diagnosis tools.

2. Image Acquisition and Preprocessing Techniques

All deep learning and ML algorithms rely on image acquisition followed by preprocessing to extract significant features for decision making. In order to achieve high accuracy in real-world deployment, a critical review of imaging devices used for the acquisition of leaf samples, along with on-field acquisition challenges with possible preprocessing approaches adopted to overcome the field challenges, is discussed in the following sections.

2.1. Imaging Devices

Leaf phenotyping monitoring relies on a range of imaging techniques, scaling from RGB to hyperspectral bands, each suited to different complex tasks. Handheld devices, particularly smartphones, remain dominant due to their imaging capabilities and computational diagnostic applications [10, 11]. At larger scales, UAVs equipped with hyperspectral, thermal, RGB, and multispectral sensors provide high-resolution with significantly larger coverage [12]. Which is already utilised for measuring leaf area index along with chlorophyll estimation using hyperspectral bands at nearly 400 to 1000 nanometres [13]. The aerial viewing ability of UAV makes it a promising technology for real-time crop health monitoring; at the same time, it is capable of covering a wider area with fine spatial detail.

2.2. Lighting, Background, and Environmental Conditions

Image acquisition techniques are facing real-time challenges like instability, propeller shadow and motion blurriness, making the image acquisition task difficult. The quality of data further degrades due to random season conditions, variation in daylight intensity and presence of background clutter. It was found that lesion contrast decreases rapidly under low light conditions, making early disease detection even more challenging. Performance deviation in terms of accuracy from 99% to 30% is observed, models previously train on control data subjected to real-time data [14].

2.3. Image Preprocessing Methods

To overcome the challenges of data acquisition, raw images are subjected to three processing steps. Which enhances the data quality and model performance. Some of the popular preprocessing techniques are discussed below:

- Noise removal: To reduce sensor noise or blur, filters like Gaussian, Median, Wiener, and Bilateral are commonly employed. Motion blur ness issues are overcome using filters such as Bilateral, Gaussian, Median and Wiener. Image is further enhanced by the deconvolution or masking [15].

- Segmentation: Real time images are often cluttered with background noise. And segmentation is an important preprocessing step that separates the reason of interest from background clutter and further enhances the classification accuracy. Previously used colour thresholding techniques are replaced by Deep segmentation models like UNet, Mask R-CNN and DeepLab as found in recent studies [16].
- Normalization: Multispectral and hyperspectral systems are often corrupted by variability between images. To overcome it, spectral normalisation, reflectance calibration and histogram equalization are common choices among the researchers [17].

After combining the above techniques, models produce cleaner and more consistent inputs, which further improves the ML and DL models' dependability in field variability or uncontrolled settings. Prominent imaging devices, along with the preprocessing approach adopted in recent studies, are shown in Table 1.

Table 1. Summary of representative studies on image acquisition and preprocessing

Reference	Imaging Device(s)	Preprocessing Methods	Notes / Outcomes
[18]	UAV-mounted hyperspectral camera (400-1000 nm)	PROSAIL inversion + Gaussian Process regression	Accurately retrieved LAI and chlorophyll.
[19]	Smartphone cameras	Mobile capture; DL classification	Citizen-science disease-diagnosis app.
[20]	High-res RGB camera	DeepLabv3+ segmentation	~0.77 IoU for wheat canopy under outdoor lighting.
[21]	RGB field images	Augmentation: brightness ±10-30%, noise	Tested CNN robustness to varied conditions.
[22]	UAV + smartphone	Super pixel segmentation	Developed a large auto-annotated dataset.

3. Datasets Used in Rice Leaf Disease Detection

The availability, diversity, and annotation quality of image datasets are important factors that determine the performance of machine learning models for the detection of rice leaf disease. Over the past ten years, advancements in dataset creation and processing have made it possible to create detection frameworks that are more accurate and widely applicable. In the following section, some important features of custom and public datasets that directly affect model performance are discussed.

3.1. Publicly Available Datasets

Publicly available sample leaf datasets play an important role in comparing different algorithms and in repeated measurements. These datasets contain high-resolution digital images of healthy and infected leaf samples taken at different geographical locations, with variable field and lighting conditions. Some benchmark datasets mostly referred to by researchers are discussed below.

- Rice Leaf Disease Detection (RLDD) Dataset: A very high-resolution image dataset consisting of both diseased and healthy leaf samples. The broader coverage and annotated data make it a benchmark dataset for deep learning and machine learning algorithms [23, 24].
- Rice Leaf Disease Image-Text Retrieval Dataset (CRLDRD): A cross-modal dataset consisting of sample images along with disease descriptions. Its purpose is to improve the interpretability of real-world challenges in leaf disease detection and to support multimodal retrieval research [25, 26].
- PlantVillage and Related Collections: Used for training single models to identify diseases of multiple plant species simultaneously. Despite being a multivariate dataset. It also includes valuable rice leaf disease samples. That are extremely useful for transfer learning experiments [27, 28].
- Existence of such a diverse dataset enhances the robustness and accuracy of disease classification models. These datasets play a vital role in increasing the cross-study comparability.

3.2. Dataset Characteristics: Size, Disease Classes, and Format

A significant variation in the dataset is observed in most of the recent studies. Some important features influencing the model evaluation and learning problem complexity are discussed below:

- Size: Open source dataset comprises 1000 to 10000 sample images. Most common publicly available datasets like DeepMulti-Net have a repository of 20000 full images, and RLDD has around 4000 images [29, 30]. Custom data sets available usually contain less images but are rich in contextual information, satisfying region-specific acquisition protocols [31, 32].
- Disease Classes: Usually, rice leaf disease datasheets have 3 to 9 classes, namely leaf blight, leaf blast, brown

spot, sheath blight and leaf smut [29, 33]. Few datasets include further sub-classifications to highlight disease severity stage and symptom morphology.

- Format: Majority of the dataset prefers image acquisition in the RGB colour space under controlled or partially controlled environments. Recent efforts also include multispectral images and paired image-text data for multimodal learning [25, 34].
- Annotation: Disease categories are commonly labelled by experts, but the level of detail and consistency can vary. A small number of datasets include hierarchical or region-level labels for detailed lesion segmentation and spatial analysis [35, 36].

3.3. Custom and Real-Time Collected Datasets

Custom datasets overcome the constraints of public corpora by encapsulating real-world variability in lighting, leaf orientation, cultivar type, and disease manifestation. These datasets are usually collected in the field via handheld cameras, UAVs, or IoT-enabled systems, making them more ecologically valid [31, 37, 38]. Examples include: collections of 3,000 to 6,000 field images organized into seven to nine disease classes [39, 40]; DepMulti-Net's 20,000-image field dataset to help deep learning models work in real-world situations [30]; and real-time IoT-based image streams for constant monitoring and quick disease response [31]. Even though these datasets show diversity in different regions, they often lack the standardization needed for large-scale benchmarking.

3.4. Dataset Challenges: Class Imbalance, Diversity, and Annotation Quality

Despite achievements in data acquisition technology, challenges were identified that restrict data set us ability and model generalization:

- Class Imbalance: Few pathogen classes, such as blast and spot, are overrepresented, whereas diseases like tungro and sheath blight are underrepresented [29, 33]. This biased the model training process. To overcome the class imbalance issue, augmentation and resampling are applied.
- Limited Diversity: Custom data sets are region-based and limited to regional and seasonal variations. This has restricted cross-study applications [41, 38].
- Annotation Quality: Overlapping infection symptoms, which are most prominent in the initial stages, may sometimes confused subjective experts, which results in label noise [25].
- Real-Time Deployment Issues: Models trained on controlled datasets frequently fail under uncontrolled field conditions where lighting fluctuations, cluttered backgrounds, and motion blur reduce accuracy [31, 39].

Community-wide efforts in multi-institutional data collection, dataset standardization, and enhanced annotation procedures are required to overcome the above-mentioned challenges.

Table 2. Summary of literature on datasets used in rice leaf disease detection

Study	Dataset Type	Size	Disease Classes	Format	Source
Rice Leaf Disease Detection Using ResNet50	Publicly Available	High-res images	Bacterial blight, Blast, Brown spot, Tungro	Images	[29]
Rice Leaf Disease Detection using Deep Learning	Publicly Available	4,199 images	5 common rice leaf diseases	Images	[42]
Deep Learning-Based Architectures for RLDD	Publicly Available	Large (varies)	Multiple rice diseases	Images	[43]
Rice Paddy Disease Detection Using CNN	Custom Collected	5,932 images	9 disease types	Images	[44]
Automatic Detection in Various Leaf Sizes	Publicly Available	4,960 images	8 rice diseases	Images	[45]
Enhancing Real-time Detection (VGG16)	Custom + Benchmark	3,611 custom images	Multiple rice diseases	Images	[39]
DepMulti-Net (Large Dataset)	Custom Collected	20,000 images	4 common rice diseases	Images	[30]
Alpha-EIOU-YOLOv8	Custom Collected	3,175 images	Blast, Leaf Folder, Brown Spot	Images	[31]
CRLDRD	Publicly Available	Cross-modal	4 common rice leaf diseases	Image and Text	[25]
Rice Leaf Disease Classification Fusion Vision	Custom Collected	2,627 images	Multiple rice leaf diseases	Images	[32]

4. Feature Extraction Techniques

Both traditional and deep learning-based rice leaf disease detection systems rely heavily on feature extraction. Deep neural representations that can learn hierarchical and task-specific features have replaced manually created appearance descriptors in this field over time.

The comparative efficacy of handcrafted, conventional, and deep feature extraction techniques is reviewed in detail in this section.

4.1. Handcrafted Features

4.1.1. Color Features

Leaf lesions are characterised by significant color variations, captured by descriptors like colour moment (mean, variance, skewness) and RGB histogram [33, 46].

These colour descriptors perform well in controlled or laboratory conditions but are unreliable in real-time applications exposed to natural lighting.

4.1.2. Texture Features

Texture analysis mainly incorporates measurements of contrast, homogeneity, entropy, and the calculation of energy from grey images. Texture features are good indicators of leaf lesions and necrosis in plants [46]. From the above-mentioned texture features, entropy and contrast are extensively used for leaf disease detection.

4.1.3. Shape Features

Researchers make use of morphological details of lesions extracted from disease contour geometry and shape descriptors, such as disease area and hue moments. Hue moments make the detection robust against rotation, scaling, and translation.

However, effectiveness falls when lesion patterns are partially covered due to clutter or having complex patterns [46]. Combining color, shape, and texture features together, an accuracy of 94% is achieved [46]. Since this model depends on handcrafted features, it is subject to field variations, limiting performance in real field conditions [47].

4.2. Traditional Feature Descriptors

The following texture-based feature descriptors provide better robustness and are preferred over handcrafted descriptors:

- Gray Level Co-occurrence Matrix (GLCM): Generates characteristics like contrast, energy, correlation, and homogeneity by capturing second-order spatial relationships. When combined with SVM or Decision Tree classifiers, GLCM-based descriptors frequently perform better than more straightforward statistical features [47].
- Histogram of Oriented Gradients (HOG): Encodes local gradient orientation patterns for identifying edges and lesion boundaries. HOG is beneficial for structural lesions but less effective for diseases with diffuse or fine-grained symptoms [48].
- Local Binary Patterns (LBP): Generates micro-texture patterns with strong illumination invariance, but performs poorly in cluttered backgrounds or overlapping infections [47].

Comparative analyses consistently demonstrated that while LBP and HOG show higher sensitivity to background complexity, GLCM features achieved higher accuracy under controlled imaging conditions.

4.3. Deep Feature Representations

Convolutional Neural Networks (CNNs): Deep CNNs greatly outperform handcrafted and conventional descriptors by enabling automatic hierarchical feature learning from raw data.

CNNs perform well on large, well-annotated datasets by capturing both low-level features and high-level semantic attributes of disease symptoms [49, 50].

4.3.1. Transfer Learning

By fine-tuning on rice disease datasets, pre-trained networks like ResNet, Inception, and VGGNet gained widespread adoption. Numerous studies have shown that transfer learning consistently increases accuracy and decreases training time, with accuracies surpassing 95% [32, 48].

4.3.2. Attention Mechanisms and Hybrid Models

Attention modules are used in more recent systems to suppress irrelevant background noise and guide the model toward pertinent lesion regions.

Attention-augmented DenseNets and CNN-LSTM combinations further improve robustness in challenging imaging scenarios [50, 51].

4.3.3. Performance Comparison and Trade-offs

Deep learning methods consistently outperform conventional methods. A 97% accuracy rate was attained by combining EfficientNet-B7 with HOG and Grad-CAM [48], whereas attention-augmented CNNs outperformed baseline architectures by 2-4% [51].

However, the use of deep models in real-time agricultural systems is limited due to high computational and annotated data requirements [30, 32].

A comparative study of feature extraction approaches is presented in Table 3.

Table 3. Feature extraction technique comparison in recent peer-reviewed studies

Feature Extraction Method	Algorithm Used	Dataset [Reference]	Accuracy (%)
RGB, Color Moments, Entropy, Shape	SVM	Public rice leaf dataset [46]	94
GLCM, LBP, HOG	Decision Tree, k-NN	Rice leaf images, custom [47]	92-94
HOG + Grad-CAM (hybrid)	EfficientNet-B7	Rice Disease Dataset (2024) [48]	97
Deep CNN (VGG19 features)	Light GBM (FVBC)	Rice Leaf DB (2,627 images) [32]	97.6
CNN + Attention (LMN)	ResNet + attention	RPDD multi-class disease (2024) [50]	97.8
CNN + ROI Extraction (DenseNet)	Hybrid	Rice Disease field images [52]	96
Multi-Level Handcrafted Features	Hybrid DL+ML	Three benchmark datasets [33]	Up to 99.5

4.4. Critical Insights and Outlook

Although crucial in early research, handcrafted and conventional descriptors are constrained by their dependence on controlled settings and manually designed features. Deep neural representations now provide state-of-the-art accuracy, especially when combined with attention and transfer learning mechanisms. However, challenges remain in enabling deployment on low-power devices and generalizing deep models to highly variable field conditions. Current research focuses on interpretable model architectures, domain adaptation, and hybrid feature extraction techniques.

4.5. Machine Learning and Deep Learning Approaches

Automatic rice leaf detection mainly follows two methodologies. In earlier works, handcrafted features were extracted in the preprocessing stage and fed into conventional machine learning classifiers. Recent trends highlight the shift of interest towards deep learning algorithms, mainly transfer learning and CNN-based models, because leaf lesion features are extracted from raw image datasets without human intervention. Although the fundamental representation learning of both ML and DL techniques is different, both techniques focus on building a classification model that is easy to implement, scalable, and accurate.

5. Machine Learning Approaches

The identification of rice leaf disease based on classical machine learning techniques requires interdependent preprocessing steps [53]. In this pipeline, the sample leaf image is subjected to image normalization followed by segmentation of the leaf lesion area for the extraction of discriminative features. In the final step, dimensionality reduction principles are applied to extract the most significant features from the feature cluster [54, 55].

When classification is performed using Random Forest, K-Nearest Neighbour (KNN), Support Vector Machines (SVM), or Naive Bayes classifiers, the overall effectiveness of the classifier is fundamentally dependent on the quality of handcrafted feature extraction [56]. It is the visual quality of features such as lesion patterns, morphological and statistical signatures, extracted that determines the classification accuracy.

5.1. Preprocessing, Segmentation, and Handcrafted Descriptors

The digital image of a sample leaf acquired is generally in RGB format. Due to variation in natural lighting conditions and shadow, RGB data can sometimes mislead the disease detection process. Therefore, the classical pipeline makes use of color transformation like RGB to HSB or RGB to YCbCr techniques, along with color histogram and morphological operations, to segment the infected leaf area from the complex background [57].

Threshold-based segmentation and clustering techniques like K-means are extensively used to extract the disease area from the surrounding healthy tissues [58, 59]. Once segmentation is implemented successfully, the following four basic handcrafted descriptors are used to characterize the infected leaf area: (1) color indices to capture chromatic distortion and hue distribution of the necrotic tissue [60]; (2) GLCM-derived texture features [61]; (3) structural descriptors like profile contour and fractal measurements from disease contour boundaries [62, 63]; and (4) frequency-domain features to discriminate microscopic details of similar disease patterns [64, 65].

The classification performance increases by carefully organizing the preprocessing. Special preprocessing techniques like noise suppression, enhancement techniques and elimination normalization increase feature stability. This tree processing becomes even more essential when samples are collected from diverse feel conditions.

5.2. Traditional Classifiers and their Behaviours

From the literature, it is evident that Support Vector Machine (SVM) is popular among researchers for its consistently high performance because of its effectiveness with small training sets in high-dimensional feature spaces [66].

In situations when extracted feature sets are heterogeneous, Random Forest and Gradient Boosting give promising results [67]. K-Nearest Neighbour techniques are distance-based algorithms effective in identifying spatial relationships but suffer performance degradation with class

imbalances [67]. Lightweight classifiers such as Naive Bayes are suitable for resource-constrained applications with a compromise in classification accuracy.

Single-descriptor type datasets perform well in laboratory conditions. Hybrid datasets comprising colour, texture, and shape descriptors outperform in the case of multi-evaluations.

These complex pipelines require domain expertise during feature extraction. Any deviation in test conditions from training conditions may deteriorate classification performance [67, 68].

5.3. Advantages and Limitations of Classical Machine Learning

Classical machine learning pipelines are particularly advantageous in small-scale sample training applications and offer faster computation [69]. Classical methods put the foundation of machine learning intelligence and are extensively used in lower-end devices and embedded systems. However, classical pipelines face challenges in preprocessing quality [70] and limited scalability [71], especially when dealing with complex pathogen structure and multi-disease datasets [72]. A detail comparative study of classical pipeline focusing on its strengths and limitations is presented in Table 4.

Table 4. Comparative analysis of machine learning techniques for rice leaf disease detection (2013-2025)

Method	Typical Accuracy	Strengths	Limitations	Key Reference(s)
SVM (RBF, Linear)	94-97.5%	Handles non-linear classes; robust to outliers	Sensitive to kernel; struggles in high-dim.	[33, 73, 74]
k-NN	80-90%	Simple; effective for low/noise data	Poor on large/heterogenous data; scalability	[75]
Decision Tree	85-92%	High interpretability	Prone to overfitting, high variance	[75]
Random Forest	95-98%	Ensemble robustness; handles multi-class	Reduced interpretability, parameter tuning	[75, 76]
Ensembles (Bagging/Boosting)	97-99%	Superior accuracy; increased generalization	Training time, complexity, and possible overfit	[75, 77]

6. Deep Learning-based Approaches

The ability of deep learning algorithms to extract the special and textual features from raw input images makes it a popular choice for the detection of rice leaf disease. The most prefer deep learning architecture is the Convolution Neural Network (CNN), because of their ability to identify local disease patterns like lesion circumference, spot and chlorotic area automatically [78].

The general procedure observed in implementing the DL algorithm is, initially, a high-capacity model is selected, followed by training through inception or using transfer learning. The model thus developed, found consistently out perform in terms of accuracy, robustness as compared to the traditional methods [24].

6.1. Convolutional Neural Networks and Transfer Learning

In DL architecture, the upper layer of the Convolutional Neural Network identifies irregularities in leaf colour due to disease. Middle layer is engaged in exploring the structural deformation that appears due to disease symptoms. Moreover, the deepest layer identify the disease-specific morphology. This multi-layer architecture facilitates rapid disease deduction with an enhanced feature set.

Whereas in transfer learning, a high-performance model, for example, VGG, AlexNet, GoogLeNet, ResNet, DenseNet, and MobileNet [79, 80] is initialized first. The rice leaf disease data set is used to fine-tune a pre-trained model. This type of transfer learning architecture results in higher classification performance even in the absence of larger data sets.

6.2. Modelling Imbalanced or Limited Data

One of the hurdles in DL training is the limited availability of rare disease datasheets, which often creates a cross-imbalance. DL overcome these hurdles by applying the following techniques.:

- Data augmentation: In this approach, the data set is artificially expanded, without introducing new images. Bhai is generating transformations like flipping and rotation, and adjusting the brightness and contrast of the image. This alteration prevents the algorithm from memorizing specific images.
- Class-balanced sampling: In this technique to approaches are used for data visualisation. Presenting rare disease samples more often, that is, over-sampling, or common disease samples are shown lesser that is, under-sampling.
- Progressive training in this approach advances in steps. First, it creates understanding by considering easy label data, followed by learning a massive pool of unlabelled or weekly labelled real-time data sets.

In the real world, leaf samples are cluttered with variations. To overcome this, GAN-based augmenters, along with a style transfer network, are used, which create variations in the dataset, similar to field variation. Thus, make the algorithm more robust to handle real-world challenges [81].

6.3. Lightweight and Edge-Deployable Architectures

Traditional deep learning models require higher and processors like GPUs and TPUs, along with a continuous and fast internet service. This makes disease detection in remote locations challenging. Thus, in such scenarios, lightweight architectures like MobileNet, ShuffleNet, EfficientNet (lighter version) and SqueezeNet are effectively utilised to overcome hardware constraints without much effecting the classification performance [82] by offering a balance between efficiency and accuracy, even for real-time field applications.

6.4. Beyond CNNs: Transformer Models and Hybrid Designs

There is a Paradigm shift pain rice leaf detection from classical CNN towards vision transformer and hybrid architectures. When an image is subjected to a CNN, it process the image using neighbourhood operation, and hence these architectures are locally based. Unlike the CNN transformer, it scans the entire leaf image and represents global context. However, transformer architecture has a limited microscopic view. The microscopic resolution capabilities of CNN combined with the long-range dependencies of the transformer are utilised in hybrid architectures. These architectures are capable of extracting special features that result in improved classifications when disease symptoms have overlapping features.

6.5. Segmentation-Aware Deep Architectures

Another recent observation reviews a shift of method from coarse image-level classification to find pixel level segmentation. Traditional classifiers assign a single label to the entire image, which makes multi-disease detection challenging. Two overcome it; a segmentation architecture is introduced in this approach, and a specific class level is assigned to individual pixels. This architecture is capable of identifying healthy reasons for different pathogen symptoms and background clitter for a given input image. It was also found that encoder-decoder architectures compress the background letter efficiently, with promising early-stage disease detection. [83, 84].

6.6. Strengths and Challenges of Deep Learning

This section highlights significant benefits and critical challenges faced during the deployment of a deep learning architecture for rice leaves disease detection.

Strength of deep learning algorithm [85]:

- In traditional ML architecture, model performance depends on the quality of handcrafted features extracted. However, in DL architecture, features are extracted automatically directly from the given input image pixels. Which results in high performance as the abstract learning of the features by the DL layer provides a generalize learning that enhances the unseen leaf features that remain unexplored by the ML architecture.
- Real-time field variations remain inherent in traditional ML architecture. DL take care of this issue by processing the image at different layers, which provide spatial hierarchies. So, DL architecture is more robust to field diversity.
- A single leaf may have multiple stages, a level pathogen. A single deep learning network can handle it easily by updating its final classification layer. DL architectures are scalable to multiple diseases.
- Early-stage disease detection is challenging as the disease symptoms are visually indistinguishable by human experts or traditional ML algorithms. DL architecture deep feature extractions with microscopic pixel-to-pixel correlation and deep contextual relationship enhance its ability to learn subtle visual clues.

Challenges in deep learning [86]:

- Millions of labelled data sets are required to prevent any mathematical error.
- Required higher and graphical processor, making standard on mobile deployment challenging.
- In case of a limited data set inquiry, the DL model may overfit by collapsing into false predictions.

The DL offer significant prediction capabilities over traditional ML models. It also offers some critical trade-offs, such as overfitting when subjected to limited data set conditions.

6.7. Integrated Perspective on ML and DL Approaches

ML and DL techniques complement each other in the automatic detection of different stages and phases of rice leaf disease. Classical pipelines suffer from limited feature engineering dependencies but provide transparency and efficiency. Deep learning requires higher-end hardware like GPUs/TPUs to process large amounts of data and requires huge labelled datasets since it starts learning from scratch.

The field rapidly integrates advanced deep learning architectures such as CNN hybrids and segmentation-aware models, which are lightweight. This technological update gives a clear picture of the shift in computer vision from classical approaches to hybrid transfer CNN models and segmentation-aware models, capable of identifying more complex diseases using representation learning.

Performance analysis of prominent DL algorithms, found in recent studies, along with the dataset used and deployment feasibility, is provided in Table 5.

Table 5. Comparison of representative deep learning models

Model/Approach [Reference]	Dataset	Accuracy (%)	F1-Score (%)	Key Features	Deployment Feasibility
VGG19 Transfer Learning [9]	Rice Leaf Image Set (6 classes)	99	98	Fine-tuned, multi-class	Mobile/UAV ready
MobileNetV2, ShuffleNet [87]	Custom field images	96-97	96	Lightweight, mobile-optimized	Edge/mobile deployments
Improved Deep Residual Networks [80]	Diverse rice disease dataset	98.7	98.7	Attention mechanism added	Medium—requires GPU/TPU
CNN+SVM Hybrid [52]	Rice Leaf Disease Images	96	95	Feature selection, classic ML	Highly adaptable, scalable
CNN-LSTM Pipeline [88, 89]	Time-series, video data	~95	-	Spatial-temporal analysis	Experimental, field pilots

7. Performance Comparison and Evaluation Metrics

A systematic approach was observed in ML and DL models for the evaluation of rice leaf disease in the past decade. More developed metrics, better reporting techniques, and benchmark procedures are in practice by researchers. However, inconsistent datasets and variation in protocols used make the comparison complicated.

7.1. Core Evaluation Metrics

Commonly used classification evaluation metrics reported for leaf disease classification are AUC, F1-score, recall, accuracy, and precision [90]. These metrics evaluate how well a classifier can differentiate between a healthy and a diseased sample. Accuracy, being intuitive, has a tendency to hide imbalanced datasets, which is mostly common in disease data.

This imbalance issue is well addressed by incorporating precision and recall, which mainly focus on how a model identifies positive cases and avoids false alarms. In studies where both correct detection and error control matter, the F1-score followed by the harmonic mean is preferred.

In the scenario where false positives and false negatives have potential costs, AUC is preferred as it evaluates the classification accuracy across the full range of thresholds [91]. It is very useful in early-stage disease detection. Some recent literature also uses specificity, especially in large-scale surveillance scenarios.

For segmentation, Intersection-over-Union (IoU) is preferred for matching the segmented area with real-time leaf segmentation.

It was found that the Matthews Correlation Coefficient (MCC) was underutilized, as it can provide better summary metrics when samples are collected from diverse fields.

7.2. Patterns in Cross-Study Comparisons

Variation in class distribution, variable daylight intensity, and non-uniformity of sample datasets make it challenging to compare different studies. However, a clear visible trend is observed: deep learning models perform well over ML models for both field-collected and laboratory datasets. Newly developed models such as DepMulti-Net, DenseNet, and MobileNetV2 report accuracy above 95%, further exceeded above 98% using curated datasets [30].

Lighter architectures such as EfficientNet-B0, MobileNetV2, and ShuffleNet are becoming popular for IoT devices due to low power consumption, despite accuracy constraints [87]. Object detection frameworks such as YOLO and R-CNN-based models perform well in identifying and classifying leaf lesions in real time, showing accuracy above 95% [23, 92].

This survey shows that when input samples are free from background clutter and with controlled lighting conditions, model performance is high. Performance decreases with the introduction of field variation samples, sometimes very significantly. There is a need for training CNN models with field-variant datasets instead of curated datasets to handle real-world challenges.

7.3. Dataset Characteristics and their Influence

Reported metrics are heavily influenced by datasets. Laboratory datasets reduce noise and enable even modest architectures to achieve near-perfect accuracy. Weaknesses in poorly regularized models are revealed by quality variability introduced by publicly sourced datasets.

Field datasets are more trustworthy measures of real-world performance. Leaf overlap, uneven illumination, and temporally varying disease symptoms challenge models assessed on such data. Studies that combine lab and field images typically demonstrate better generalization.

Table 6. Summary of representative peer-reviewed research (past ten years)

Reference	Model	Dataset (Test zone)	Evaluation Metrics	Key Performance Outcomes
[30]	DepMulti-Net	Four rice diseases (lab)	Accuracy	98.56% accuracy
[80]	CBAM-based DRSN	Three rice diseases (lab/field)	mAP, Accuracy, Recall	98.89% mAP, 98.65% accuracy
[87]	MobileNetV2, ShuffleNet	Public & real-field images	Accuracy, F1-score, AUC	>96% accuracy, high F1/AUC
[79]	ResNet197	Combined crop leaf dataset	Accuracy	99.58% accuracy
[24]	Faster R-CNN	Online + in-field datasets	Accuracy, Real-time performance	>95% accuracy, real-time
[51]	DenseNet, U-Net hybrid	ROI-focused, lab images	Accuracy	96% accuracy
[76]	SVM, RF, KNN, VGG16	Laboratory images	Accuracy, Precision, Recall, MCC	>95% accuracy, diverse metrics
[47]	DeepBatch Ensemble	Field/lab mixed	Accuracy, F1-score	>97% accuracy, strong F1

7.4. Benchmark Models and Reproducibility Issues

Presently, the three models most widely adopted by researchers as de facto benchmarks are: ResNet50 and its higher variants for high classification accuracy demands; ShuffleNet and MobileNetV2 for smartphone/IoT devices in limited-resource scenarios; and SVM with manual feature extraction as the classical ML baseline. These models are well-documented, compatible with transfer learning, and easily accessible. However, they often suffer from reproducibility issues due to imbalanced public datasets and a lack of proper documentation of experimental setup and protocols. To achieve architectural development, there is a need for standardize multi species open access data set. All possible architectures must be evaluated using a common data set for a coherent and fair validation. Recent models with key performance features are tabulated in Table 6.

8. Conclusion

This survey extensively reviews modern AI algorithms, which highlights the ultimate challenges faced in the real-world deployment. This survey critically reviews each step of the image processing-based DL system from initial image acquisition to final deployment of the intelligent model, with an emphasis on future research. In the course of this survey, it is discovered that automatic disease detection is a developing research area and training the model in controlled laboratory conditions presents serious deployment challenges in real field conditions and ease of major concerns. This survey also took into consideration the different image sensing modalities from aerial to terrestrial, available for leaf disease detection. As the image acquisition process directly affects the data set quality and hence the model performance, the geographical, seasonal and daylight intensity variation for the makes the data acquisition more challenging. Lightweight classical ML algorithms are still popular in smartphones, IoT and embedded applications, but with a compromise in performance. In the absence of hardware constraints, DL architectures like CNN and transfer learning-based algorithms are the prime choice among researchers because of their self-learning ability. A clear shift of interest from handcrafted features to end-to-end architectures is observed in the recent leaf disease classification algorithm. It was found that some of the hybrid algorithms and a few attention mechanisms perform exceptionally better than conventional CNN models when feed with a balanced and curated dataset. Small data sets and a lack of standardized evaluation metrics mix the development of automatic rice leaf disease detection, challenging and providing an I-score for future research. It was further observed that some classifiers neglect failure evaluations; the question of why the classifier fails in correct detection remains unanswered. Classifier false positive prediction leads to the agronomical resource wastage and false negatives, delaying the treatment process. These limitations make real-time field implementation difficult. Now, in order to incorporate early disease warning capabilities, multispectral and hyperspectral imaging outperformed RGB-based data acquisitions. The rice leave detection is a reproductive research process, vision based AI approach enable repeated disease monitoring which again involves a need of open access standard data set, with supportive policies framework for Cross study verification and development of AI based rice leaf disease detection. Overall, the available literature suggests a potential but incomplete deviation of experimental models to operational agricultural products. This requires a combined and aligned effort of data scientists, agronomists and the Pharma community. That will result in a cognitive AI-driven rice disease detection system capable of making fair decisions even in diverse field conditions.

Conflicts of Interest

No conflict of interest.

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