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Automated Rice Crop Health Monitoring: A Review of Deep Learning Diseased Leafs Detection and Classification Models.

DANLADI SHEMANG KAJE[1], PROF. A.Y GITAL[2], LAWAL ABDULLAHI RUKUNA[3], GRACE OJOCHENEMI EMMANUEL ANORUE[4], PAUL AGADA[5]
[1, 2, 3]Department of Computer Science, Abubakar Tafawa Balewa University, Bauchi State, Nigeria
[4]Computer Science Department, School of Secondary Education (Science), Federal College of Education (Technical) Gombe
[5]Department of information and communication Technology, Plateau State University, Bokkos, Plateau State.

Abstract- One of the common global vital foods is rice. As important and widespread at it is, it faces significant productivity challenges due to the impact common plant diseases such as bacterial blight, brown spot, and rice blast, which compromise yield and quality in millions of tons worldwide. Relying on manual inspections as a traditional method for disease detection, are often subjective, time-consuming, and subject to errors. The field or Artificial Intelligence in the sub field of deep learning has emerged as a transformative technology for automating disease detection and classification, offering high accuracy and efficiency. This paper provides a comprehensive review of deep learning techniques, including convolutional neural networks, and transfer learning approaches, applied to rice disease detection. Advancements in the design of algorithms, dataset usage, and real-world applications are discussed. Overlapping symptoms, overfitting, and scalability and diverse field conditions are challenges being highlighted, along with proposed solutions. The review emphasizes the need for models that are scalable, diverse datasets, and real-time deployment for practical implementation. Multi-modal systems, lightweight architectures for resource-constrained environments, and integration with precision agriculture systems are the focus for future directions. This work aims to bridge the gap between technological advancements and practical application, contributing to sustainable agricultural practices and global food security.

Index Terms- Deep Learning, Convolutional Neural Networks, Transfer Learning, Disease Detection, Disease Classification

I. INTRODUCTION

Rice is a cornerstone of global food security, serving as the primary staple food for more than half of the world's population (Mohidem et al., 2022). As one of the most widely cultivated crops, rice plays a pivotal role in sustaining livelihoods, particularly in Asia and Africa, where it is both a major food source and a significant contributor to economic stability (Dorairaj & Govender, 2023). However, the productivity of rice is heavily compromised by the prevalence of various diseases, including bacterial blight, brown spot, rice blast, and sheath blight. These diseases not only reduce crop yield but also deteriorate grain quality, leading to substantial economic losses and threatening global food security (Senapati et al., 2022).

Timely detection and accurate diagnosis of rice diseases are essential for effective management and control (Venu Vasantha et al., 2022). Traditionally, farmers and agricultural experts rely on manual field inspections to identify diseases, which are inherently subjective, time-consuming, and often inaccurate. Factors such as variability in disease symptoms, environmental conditions, and human expertise can result in delayed or incorrect diagnosis, exacerbating the impact of diseases on crop health and yield (John et al., 2023).

In recent years, the integration of advanced technologies in agriculture has opened new avenues for addressing these challenges (Yadav et al., 2023). Among these, deep learning, a subfield of artificial intelligence, has emerged as a powerful tool for automating complex tasks such as image recognition and classification (Mathew, 2024). Adopting convolutional neural networks CNNs and other deep learning architectures, researchers have developed models capable of identifying and classifying plant diseases with remarkable precision, often surpassing human-level performance (Sutaji & Rosyid, 2022). The adoption of such technologies in rice disease detection offers the potential to revolutionize traditional practices, enabling early diagnosis, targeted intervention, and improved decision-making (Gülmez, 2024).

The aim of this paper is to provide a comprehensive review of deep learning algorithms for rice disease detection and classification. It examines the evolution of these technologies, highlighting the advancements in algorithm design, dataset availability, and real-world applications. Key challenges, such as dataset variability, model generalizability, and computational efficiency, are also discussed. The paper concluded by outlining future directions for research, emphasizing the need for innovative solutions to close existing gaps and achieve scalable, real-time implementation in agricultural systems.

II. RESEARCH METHODOLOGY

This outlines the structured approach used to investigate deep learning algorithms for rice disease detection and classification. The methodology involves a systematic literature search, the application of selection criteria, and an in-depth analysis of relevant studies. This study adopts a systematic approach to explore and analyze the application of deep learning algorithms for rice disease detection and classification.

2.1 Literature Search

The research began with an comprehensive literature search also aimed at identifying relevant studies published between 2018 to 2024. The time frame was chosen to include recent advancements in the field. The search was conducted across multiple scientific databases, including Frontiers, ResearchGate, IEEE, Springer, Elsevier's ScienceDirect, and Google Scholar, which are well-known for hosting high-quality research journals in computer vision, artificial intelligence, and agricultural applications.

A set of keywords were used to ensure the search focused on deep learning approaches for rice disease detection. Keywords included "rice disease detection," "deep learning in agriculture," "CNN for rice diseases," "transfer learning in plant health," and "AI-based rice disease classification." Boolean operators were employed to refine the search, ensuring comprehensive coverage of relevant studies while excluding irrelevant results.

2.2 Selection Criteria

To ensure that only relevant and high-quality studies were included, specific inclusion and exclusion criteria were applied during the screening process.

Inclusion Criteria: The study focused explicitly on rice diseases and their detection or classification. The research employed deep learning techniques, such as Convolutional Neural Networks, transfer learning-based models, or hybrid approaches. Papers reporting experimental validation with performance metrics, such as accuracy, precision, recall, F1-score, or computational efficiency. The studies utilized publicly available or proprietary datasets, with sufficient detail on data characteristics and preprocessing methods.

Exclusion Criteria: Studies addressing plant disease detection in general without specific focus on rice. Research lacking practical implementation or empirical validation. Papers relying on traditional machine learning approaches without using deep learning architectures. Reviews or theoretical articles without experimental contributions.

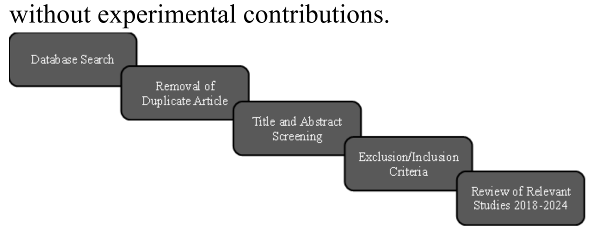

Figure 1: Article Selection Procedure

III. RELATED WORK

The application of deep learning in agriculture, particularly in rice disease detection and classification,

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has gained significant attention in recent years. Various techniques and architectures have been explored by researchers to address challenges such as early disease detection, classification accuracy, and real-time deployment.

(Deng et al., 2021) proposed an automatic diagnosis method for rice diseases using a deep learning-based ensemble model that integrates DenseNet-121, SE-ResNet-50, and ResNeSt-50. The model was trained on a dataset of 33,026 images representing six rice diseases, including leaf blast, false smut, neck blast, sheath blight, bacterial stripe disease, and brown spot. The ensemble model achieved an accuracy of 91% in diagnosing these diseases, demonstrating its effectiveness even in cases where visual similarities among diseases posed challenges. To facilitate practical application, the model was implemented in a smartphone app, allowing users to upload images of rice plants for web-based analysis. This study highlights the potential of deep learning models to provide accurate, accessible, and efficient tools for disease management in rice cultivation.

A machine learning algorithm was developed by (Ramesh & Vydeki, 2018) to detect and classify rice blast disease, a significant threat to global rice production. Their approach involved capturing images of both healthy and blast-affected rice leaves, extracting relevant features, and utilizing a dataset of 300 images for training and testing purposes. The proposed system achieved an accuracy of 99% for detecting blast-infected images and 100% for normal images during the training phase, demonstrating its potential for early disease detection to prevent substantial economic losses for farmers.

(Shrivastava et al., 2019) developed a rice plant disease classification system utilizing transfer learning with deep convolutional neural networks They collected 619 field images categorized into four classes: Rice Blast, Bacterial Leaf Blight, Sheath Blight, and Healthy Leaves. A pre-trained CNN served as a feature extractor, and a Support Vector Machine functioned as the classifier. The system achieved promising results, indicating its potential for early disease detection and as a preventive measure in agricultural practices. The authors suggest that this approach could be extended to develop a comprehensive rice plant disease identification system for real-world agricultural fields.

(Patidar et al., 2020) employ a deep residual learning-based system for detecting and classifying rice plant diseases, focusing on Bacterial Leaf Blight, Brown Spot, and Leaf Smut. Utilizing a dataset of rice leaf images, they employed a pre-trained ResNet model to extract features, followed by a Softmax classifier for categorization. The system achieved high accuracy in identifying the specified diseases, demonstrating the effectiveness of deep residual learning in agricultural disease detection. The authors suggest that this approach could be extended to develop a comprehensive rice plant disease identification system for real-world agricultural fields.\

(Ahad et al., 2023) conducted a comprehensive review of convolutional neural network (CNN) applications in rice disease recognition, emphasizing advancements in accuracy, speed, and deployment on mobile devices. They highlighted the effectiveness of CNNs in extracting features from rice disease images, leading to improved identification and classification. The study also discussed the development of lightweight CNN models suitable for real-time applications and mobile deployment, enhancing the practicality of these technologies in agricultural settings. The authors underscored the importance of ensemble learning and transfer learning techniques in further enhancing model performance. They concluded that CNN-based approaches offer significant potential for efficient and accurate rice disease recognition, contributing to better disease management and crop yield optimization.

(Hasan et al., 2019) developed an automated system for identifying and classifying nine distinct rice diseases by integrating a Support Vector Machine with a Deep Convolutional Neural Network. They utilized transfer learning to enhance the model's performance, training it on a dataset of 1,080 images. The combined approach achieved an accuracy of 97.5%, demonstrating its potential to assist farmers in early disease detection and management.

(Y. Wang et al., 2021) introduced an attention-based depthwise separable neural network optimized with Bayesian methods (ADSNN-BO) for detecting and

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classifying rice diseases from leaf images. Their model, built upon the MobileNet architecture and enhanced with an attention mechanism, was trained and validated on a public dataset comprising four categories: healthy leaves, bacterial leaf blight, brown spot, and leaf smut. The ADSNN-BO model achieved a classification accuracy of 95.78%, outperforming several existing models in both accuracy and computational efficiency. This research underscores the potential of combining attention mechanisms with lightweight neural networks for effective and efficient plant disease detection.

A deep learning-based multi-classification model was developed by (Singla et al., 2022) for rice disease detection, focusing on accurately identifying various rice leaf diseases. Their approach utilized a convolutional neural network (CNN) architecture trained on a dataset of rice leaf images, encompassing multiple disease categories. The model achieved high accuracy in classifying different rice diseases, demonstrating its potential as a reliable tool for early detection and management in agricultural practices. The authors suggest that this model can assist farmers and agronomists in implementing timely interventions to mitigate crop losses due to diseases.

(Prajapati et al., 2017) developed a prototype system for detecting and classifying rice plant diseases using image processing and machine learning techniques. Focusing on three diseases Bacterial Leaf Blight, Brown Spot, and Leaf Smut—they captured images of infected rice plants and evaluated various background removal and segmentation methods. The authors introduced a centroid-feeding-based K-means clustering algorithm to segment the diseased portions of leaf images, followed by the removal of green pixels to enhance segmentation accuracy. They extracted color, shape, and texture features from the segmented images and employed a Support Vector Machine (SVM) for multi-class classification. The system achieved 93.33% accuracy on the training dataset and 73.33% on the test dataset, with 5-fold and 10-fold cross-validation accuracies of 83.80% and 88.57%, respectively. This research demonstrates the potential of combining image processing with machine learning for effective rice disease detection and classification.

(Ahmed et al., 2019) proposed a machine learning-based system to detect three prevalent rice leaf diseases: leaf smut, bacterial leaf blight, and brown spot. Utilizing clear images of affected rice leaves, they applied algorithms including K-Nearest Neighbour (KNN), Decision Tree (J48), Naive Bayes, and Logistic Regression. The Decision Tree algorithm, after 10-fold cross-validation, achieved an accuracy exceeding 97% on the test dataset, demonstrating the system's potential to assist farmers in timely disease identification and management.

(P. Narmadha et al., 2022) introduced a deep learning-based model for detecting rice plant diseases, specifically targeting Bacterial Leaf Blight, Brown Spot, and Leaf Smut. Their approach utilized a Densely Convolutional Neural Network (DenseNet169) combined with a multilayer perceptron MLP. The process began with image preprocessing, including channel separation, grayscale conversion, and noise removal via median filtering. Subsequently, the fuzzy c-means algorithm segmented the diseased portions of the rice leaf images. Features were extracted using the pretrained DenseNet169 model, and classification was performed by replacing the final layer with an MLP. Evaluated on a benchmark dataset, the model achieved a maximum accuracy of 97.68%, outperforming several existing methods. This study highlights the potential of combining deep transfer learning with advanced preprocessing and segmentation techniques for effective rice plant disease detection.

(Sethy et al., 2020) developed a method for identifying rice leaf diseases by combining deep feature extraction with Support Vector Machine SVM classification. They introduced a dataset of 5,932 field images covering four rice leaf diseases: bacterial blight, blast, brown spot, and tungro. The study evaluated 11 Convolutional Neural Network models through transfer learning and deep feature extraction, followed by SVM classification. Results indicated that deep feature extraction combined with SVM outperformed transfer learning alone. Notably, the ResNet50 model's deep features, when paired with SVM, achieved an F1 score of 0.9838. Additionally, the study compared CNN-based models with traditional image classification methods, finding superior performance in the former.

(Shrivastava & Pradhan, 2021) proposed a machine learning approach for classifying rice plant diseases using color features extracted from leaf images. They focused on three diseases: Brown Spot, Leaf Blast, and Bacterial Leaf Blight. The study involved capturing images of infected leaves, preprocessing them to extract color features, and employing classifiers such as Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Decision Tree. Among these, the SVM classifier achieved the highest accuracy, demonstrating the effectiveness of color features in distinguishing between different rice plant diseases.

(Andrianto et al., 2020) developed a smartphone application utilizing deep learning for rice plant disease detection. The system employs a convolutional neural network to analyze images of rice plants, identifying diseases such as bacterial leaf blight, brown spot, and leaf smut. The application enables farmers to capture leaf images in the field, receive immediate diagnostic results, and access treatment recommendations. This mobile solution aims to enhance early disease detection and management in rice cultivation, contributing to improved crop health and yield

(Upadhyay & Kumar, 2022) introduced a novel approach for classifying rice plant diseases using a deep convolutional neural network. Their method involves preprocessing leaf images to remove background noise through Otsu's global thresholding technique, followed by training a fully connected CNN on a dataset comprising 4,000 images for each category: healthy leaves, leaf smut, brown spot, and bacterial leaf blight. The proposed model achieved high accuracy in disease classification, demonstrating the effectiveness of deep learning techniques in agricultural disease detection.

(F. Jiang et al., 2020) proposed a method for identifying four rice leaf diseases by combining deep learning with support vector machines (SVM). They utilized convolutional neural networks (CNNs) to extract features from images of diseased rice leaves and then applied SVM for classification. Through 10-fold cross-validation, the optimal SVM parameters were determined, resulting in an average recognition accuracy of 96.8%. This performance surpassed that of traditional backpropagation neural network models, indicating the effectiveness of integrating CNNs with SVM for crop disease diagnosis.

A deep learning based system was developed by (Kiratiratanapruk et al., 2020) to detect rice diseases from field images. They applied a convolutional neural network to identify six major rice diseases, achieving high accuracy in disease detection. This approach demonstrates the potential of deep learning techniques in enhancing agricultural disease management.

(Bhattacharya et al., 2020) developed a convolutional neural network framework to automatically classify three types of rice leaf diseases: Brown Spot, Leaf Blast, and Bacterial Leaf Blight. Their approach involved training a CNN model on a dataset of labeled rice leaf images, enabling the system to accurately identify and distinguish between the specified diseases. The study demonstrated that deep learning techniques, particularly CNNs, are effective in plant disease classification, offering a potential tool for precision agriculture and early disease detection. The authors suggest that such automated systems can assist farmers in timely disease management, potentially improving crop yield.

(Bari et al., 2021) developed a real-time system for diagnosing rice leaf diseases using a Faster Region-based Convolutional Neural Network (Faster R-CNN). Their model effectively identified three common rice diseases rice blast, brown spot, and hispa with accuracies of 98.09%, 98.85%, and 99.17%, respectively. Additionally, it recognized healthy rice leaves with 99.25% accuracy. This approach demonstrates the potential of deep learning techniques in enhancing agricultural disease management.

A deep neural network model was proposed by (Daniya & Vigneshwari, 2022) for detecting rice plant diseases by integrating texture and deep features. Their approach combined traditional texture analysis with deep learning techniques to enhance the accuracy of disease detection. The model was trained and tested on a dataset of rice leaf images, achieving high accuracy in identifying various diseases. This study demonstrates the effectiveness of combining texture features with deep learning for improved plant disease detection.

(Simhadri & Kondaveeti, 2023) explores the application of transfer learning with pre-trained convolutional neural network models to identify rice leaf diseases. The authors evaluated 15 pre-trained CNN architectures, including InceptionV3, ResNet-50, and AlexNet, to classify ten categories: nine rice diseases—Bacterial Leaf Blight, Brown Spot, Hispa, Leaf Blast, Leaf Scald, Leaf Streak, Narrow Brown Spot, Sheath Blight, and Tungro—and healthy leaves. Their findings indicate that the InceptionV3 model outperformed others, achieving an average accuracy of 99.64%, with precision, recall, F1-score, and specificity values of 98.23, 98.21, 98.20, and 99.80, respectively. In contrast, the AlexNet model demonstrated comparatively lower performance, with an average accuracy of 97.35%. The study underscores the effectiveness of transfer learning in enhancing the accuracy and efficiency of rice leaf disease detection, offering a promising solution for timely and precise disease management in agriculture.

IV. DEEP LEARNING ALGORITHM FOR RICE DISEASE DETECTION

Deep learning has significantly advanced rice disease detection by automating feature extraction and classification tasks(Wani et al., 2022). Unlike traditional methods requiring handcrafted features, deep learning models process raw image data to identify disease-specific patterns with high accuracy. These models, such as neural networks, extract features layer by layer, from simple textures to complex disease signatures, enabling effective identification of rice diseases like brown spot and bacterial leaf blight(Shoaib et al., 2023).

A major strength of deep learning is its adaptability to agricultural datasets (Cravero et al., 2022). Techniques like transfer learning allow pre-trained models (e.g., ResNet and EfficientNet) to be fine-tuned for rice diseases, achieving high performance even with limited datasets (Yusuf et al., 2024). Additionally, data augmentation methods, such as rotation and scaling, improve model robustness in diverse real-world conditions (Mumuni & Mumuni, 2022).

Despite their potential, deep learning models face challenges, including high computational requirements and limited interpretability. These constraints impact deployment in resource-limited settings and raise concerns about decision-making transparency. Addressing these issues through lightweight architectures, and improved datasets, is essential for broader adoption.

(Simhadri & Kondaveeti, 2023) explores the application of transfer learning with pre-trained convolutional neural network models to identify rice leaf diseases. The authors evaluated 15 pre-trained CNN architectures, including InceptionV3, ResNet-50, and AlexNet, to classify ten categories: nine rice diseases Bacterial Leaf Blight, Brown Spot, Hispa, Leaf Blast, Leaf Scald, Leaf Streak, Narrow Brown Spot, Sheath Blight, and Tungro and healthy leaves. Their findings indicate that the InceptionV3 model outperformed others, achieving an average accuracy of 99.64%, with precision, recall, F1-score, and specificity values of 98.23, 98.21, 98.20, and 99.80, respectively. In contrast, the AlexNet model demonstrated comparatively lower performance, with an average accuracy of 97.35%. The study underscores the effectiveness of transfer learning in enhancing the accuracy and efficiency of rice leaf disease detection, offering a promising solution for timely and precise disease management in agriculture.

(Ritharson et al., 2024)presents a novel approach to accurately identify and classify various subtypes of rice leaf diseases using deep learning and transfer learning techniques. The authors developed a model named DeepRice, which leverages deep feature extraction and classification methods to distinguish between different rice leaf disease subtypes. The model was trained and tested on a comprehensive dataset comprising images of rice leaves affected by various diseases. DeepRice achieved an overall accuracy of 97.8%, with precision, recall, and F1-scores exceeding 96% across all tested subtypes. This performance highlights the potential of deep learning in providing precise and reliable tools for agricultural disease management.

(Mahadevan et al., 2024) introduces an advanced method for detecting rice leaf diseases by integrating deep learning techniques with enhanced image processing algorithms. The proposed system employs a Deep Spectral Generative Adversarial Neural Network DSGAN2 combined with an Improved

Threshold Neural Network ITNN to enhance image quality. This is followed by segmentation using a Segment Multiscale Neural Slicing SMNS algorithm, which identifies color saturation in the enhanced images. Optimal features are then selected using the Spectral Scaled Absolute Feature Selection S2AFS method, and feature weight values are analyzed through the Social Spider Optimization to select the Feature with the Closest Weight S2O-FCW)algorithm. Finally, the DSGAN2 algorithm detects rice plant diseases based on the selected features. The results demonstrate that the proposed DSGAN2 system significantly reduces the false rate compared to existing systems: ACPSOSVM-Dual Channels Convolutional Neural Network (APS-DCCNN): 55.2%, AlexNet: 50.4%, Convolutional Neural Network: 49.5%.

(Mandwariya & Jotwani, 2024) proposes a method utilizing pre-trained Deep Convolutional Neural Networks DCNNs to accurately identify and classify rice leaf diseases. The study focuses on detecting eleven categories, including healthy leaves and ten disease types such as leaf blast, brown spot, bacterial blight, false smut, neck blast, stem borer, tungro, hispa, and BPH.The authors evaluated several advanced architectures, including XceptionNet, ResNet50, DenseNet, VGG19, and SqueezeNet, along with optimization techniques such as SGDM, ADAM, and RMSprop. Among these, DenseNet combined with the ADAM optimizer achieved the best results, with an overall accuracy of 98.5%. Precision, recall, and F1-scores for all categories exceeded 97%. The study demonstrates the effectiveness of combining transfer learning with baseline learning for rice disease detection, offering a promising solution for real-time, automated disease diagnosis, which is critical for timely intervention and improved agricultural practices.

An enhanced version of YOLOv8 model was introduce by (Trinh et al., 2024) to detect rice leaf diseases more effectively. The authors propose a two-stage approach: Data Collection and Preparation: Images of rice leaves affected by diseases such as blast leaf, leaf folder, and brown spot are automatically collected and categorized. Model Training and Deployment: The modified YOLOv8 model, incorporating a combination of EIoU loss and α-IoU loss functions, is trained on the prepared dataset. This trained model is then deployed on IoT devices for real-time detection and identification of rice leaf diseases. Experimental results demonstrate that the proposed model achieves an accuracy of 89.9% on a dataset comprising 3,175 images, outperforming existing methods such as YOLOv7 and YOLOv5.

Table1: Summary of reviewed literatures

Author	Method	Accuracy	Limitation
(Deng et al., 2021)	Ensemble model integrating DenseNet-121, SE-ResNet-50, and ResNeSt-50; smartphone app for diagnosis.	91.00%	Limited to six rice diseases; challenges with visual similarity among diseases.
(Ramesh & Vydeki, 2018)	Machine learning model with feature extraction from 300 images of healthy and diseased leaves.	99.00%	limited dataset (300 images); limited generalizability to other diseases or environments.
(Shrivastava et al., 2019)	Transfer learning with pre-trained CNNs and SVM for classifying four rice diseases.	91.37	reliance on pre-trained models with potential constraints on adaptability.

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(Patidar et al., 2020)	Deep residual learning with ResNet for detecting bacterial leaf blight, brown spot, and leaf smut.	95.83	Limited scalability to other diseases or real-world conditions.
(Ahad et al., 2023)	Reviewed CNN applications for rice disease detection; highlighted ensemble learning and transfer learning techniques.	98.00%	Lacks implementation details; focused on review rather than new methodology.
(Hasan et al., 2019)	Deep CNN integrated with SVM; transfer learning used on 1,080 images.	97.50%	limited dataset
(Y. Wang et al., 2021)	Attention-based depthwise separable neural network (ADSNN-BO) optimized with Bayesian methods.	95.78%	Limited to four categories; scalability to broader datasets not addressed.
(Singla et al., 2022)	Multi-class CNN model for detecting and classifying rice diseases.	98.86	Lack of details on dataset size and diversity; challenges in handling overlapping symptoms.
(Prajapati et al., 2017)	K-means clustering for segmentation, SVM for classification of three rice diseases.	73.33%	Overfitting
(Ahmed et al., 2019)	Utilized KNN, Decision Tree, Naive Bayes, and Logistic Regression for detecting three diseases.	97.00%	Limited to three diseases; performance dependent on dataset quality.
(P. Narmadha et al., 2022)	DenseNet-169 and MLP combined with preprocessing techniques and fuzzy c-means segmentation.	97.68%	May be computationally expensive for deployment.
(Sethy et al., 2020)	Deep feature extraction with CNNs and SVM classification.	F1 Score 98.38%	Potential overfitting
(Shrivastava & Pradhan, 2021)	Color feature extraction from leaf images with SVM, KNN, and Decision Tree classifiers.	94.65	Limited feature set
(Andrianto et al., 2020)	Smartphone app with CNN for real-time rice disease detection.	60.00%	Overfitting

(Upadhyay & Kumar, 2022)	Preprocessed leaf images using Otsu's thresholding; trained a fully connected CNN on 4,000 images per category.	99.70%	No discussion on dataset diversity.
(F. Jiang et al., 2020)	CNN for feature extraction combined with SVM for classification of four rice diseases.	96.80%	Limited to four diseases;
(Kiratiratanapruk et al., 2020)	CNN for detecting six major rice diseases from field images.	79.91%	Lack of details on dataset and deployment; potential challenges in field variability.
(Bhattacharya et al., 2020)	CNN framework for classifying brown spot, leaf blast, and bacterial leaf blight.	94.00%	Limited to three diseases; lacks evaluation under real-world conditions.
(Bari et al., 2021)	Faster R-CNN for detecting rice blast, brown spot, and hispa in real time.	99.25%	Limited to three diseases;
(Daniya & Vigneshwari, 2022)	Combined texture analysis with CNN-based deep learning for disease detection.	95.20%	Lack of scalability testing
(Simhadri & Kondaveeti, 2023)	Transfer learning with 15 pre-trained CNN architectures for detecting ten categories of rice diseases.	99.64%	High reliance on pre-trained models; dataset diversity not clearly addressed.
(Ritharson et al., 2024)	DeepRice model using transfer learning and deep feature extraction for disease classification.	97.80%	Scalability and dataset diversity not discussed.
(Mahadevan et al., 2024)	DSGAN2 integrated with advanced image processing for rice disease detection.	99	High computational complexity
(Mandwariya & Jotwani, 2024)	Pre-trained DCNNs with optimization techniques for detecting 11 rice diseases.	98.50%	Limited discussion on dataset generalizability and real-time testing.
(Trinh et al., 2024)	Enhanced YOLOv8 with EIoU and α-IoU loss functions for real-time detection.	89.90%	Performance lower than some advanced models

4.1 Convolutional Neural Network CNN

Convolutional Neural Networks are a cornerstone of deep learning for rice disease detection, renowned for their ability to process image data effectively (Daniya & Vigneshwari, 2023). CNNs extract disease-specific features directly from images, bypassing the need for manual feature engineering (Mall et al., 2023). By processing data through layers of convolution and pooling, CNNs identify patterns such as lesions, discoloration, and textures, which are indicative of diseases like bacterial leaf blight and brown spot (V et al., 2024).

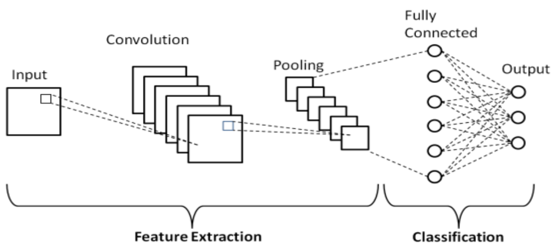

Figure 2: Basic convolutional neural networks (Phung & Rhee, 2019)

Advanced CNN architectures like ResNet, DenseNet, and MobileNet have shown impressive performance in rice disease detection (Dutta et al., 2024). ResNet mitigates the vanishing gradient problem through skip connections, enabling deeper networks to perform well (Borawar & Kaur, 2023). DenseNet improves feature sharing between layers, while MobileNet's lightweight design is ideal for real-time applications, especially in resource-limited environments (Hadi et al., 2024). CNN-based systems often achieve accuracies above 95%, showcasing their reliability in classification tasks.

4.2 Transfer Learning

Transfer learning is a widely adopted approach in rice disease detection, particularly when datasets are limited or insufficient for training deep learning models from scratch (Shamsuzzaman, 2022). This technique employs pre-trained models, originally designed for large-scale image classification tasks, and fine-tunes them for specific applications such as identifying rice diseases. By reusing knowledge from pre-trained networks, transfer learning significantly reduces computational costs and training time while improving model performance (Hamhongsa et al., 2023).

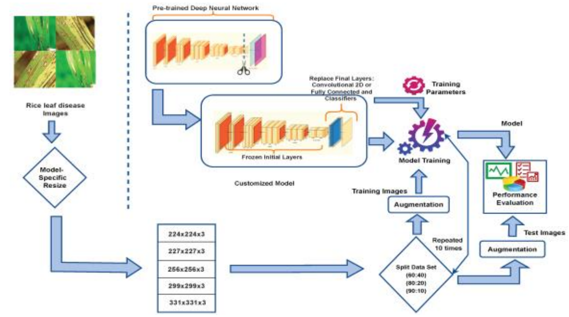

Figure 3: automatic recognition of rice leaf diseases using transfer learning (Simhadri & Kondaveeti, 2023)

Popular architectures used in transfer learning include VGGNet, ResNet, Inception, and EfficientNet (Hassan et al., 2021). These models, pre-trained on extensive datasets like ImageNet, provide a strong foundation for feature extraction (Saxena et al., 2020). For rice disease detection, the initial layers of these networks retain their learned general features (such as edges and textures), while the deeper layers are fine-tuned to recognize disease-specific patterns on rice leaves. This adaptation enables the models to achieve high accuracy even with relatively small datasets (Simhadri et al., 2024a).

V. DATASET USAGE AND REAL-WORLD APPLICATION

Publicly available datasets play a crucial role in advancing research on rice disease detection by providing standardized benchmarks for training and evaluating deep learning models (Yu & Zheng, 2024a). These datasets are often comprised of labeled images of healthy and diseased rice leaves, enabling researchers to build and test algorithms under controlled conditions (Simhadri et al., 2024b). They vary in size, disease coverage, and image quality, which directly impacts model generalization and accuracy. The following datasets have been widely utilized in rice disease detection research:

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Table 2: Datasets used

Authors	Dataset Used	Diseases Type
(Deng et al., 2021)	Manually collected	leaf blast, leaf smut, neck blast, sheath blight, bacterial stripe disease, and brown spot.
(Ramesh & Vydeki, 2018)	Manually collected	Rice blast
(Shrivastava et al., 2019)	Manually collected	Rice blast, bacterial leaf blight, sheath blight, healthy leaves
(Patidar et al., 2020)	https://archive.ics.uci.edu/ml/datasets/Rice+Leaf+Diseases.	Bacterial leaf blight, brown spot, and leaf smut
(Ahad et al., 2023)	University of California Irvine Machine Learning Repository/ Bangladesh Rice Research Institute	Bacteria blight, leaf smut, brown spot, tungro, blight, leaf blast, hispa, sheath blight
(Hasan et al., 2019)	Manually Collected	Bacterial leaf blight, rice blast, brown spot, false smut, leaf smut, red stripe, leaf scald, sheath blight and tungro.
(Y. Wang et al., 2021)	Public availably	Brown spot, rice hispa damage, leaf blast, healthy
(Singla et al., 2022)	-	8
(Prajapati et al., 2017)	Manually collected	Bacterial leaf blight, brown spot, and leaf smut

(Ahmed et al., 2019)	https://archive.ics.uci.edu/ml/datasets/Rice+Leaf+Diseases	leaf smut, bacterial leaf blight and brown spot
(P. Narmadha et al., 2022)	https://archive.ics.uci.edu/ml/datasets/Rice+Leaf+Diseases	bacterial leaf blight, brown spot, and leaf smut
(Sethy et al., 2020)	Manually collected	Bacterial blight, blast, brown spot and tungro
(Shrivastava & Pradhan, 2021)	from the real agriculture field	Bacterial leaf blight, rice blast, sheath blight, healthy leave
(Andrianto et al., 2020)	Manually collected	hispa, leaf blast, brown spot, and healthy
(Upadhyay & Kumar, 2022)	https://archive.ics.uci.edu/ml/datasets/Rice+Leaf+Diseases	leaf smut, brown spot, bacterial leaf blight
(F. Jiang et al., 2020)	Manually collected	Healthy, rice blast, rice bacterial spot, rice streak leaf spot, rice sheath blight
(Kiratiratanapruk et al., 2020)	Manually collected	blast, bacterial leaf blight, brown spot, narrow brown spot, bacterial leaf streak and rice ragged stunt virus
(Bhattacharya et al., 2020)	Collected online (Internet)	Bacterial blight, blast, and brown mark
(Bari et al., 2021)	Manually Collected	Rice blast, brown spot, and hispa
(Simhadri & Kondaveeti, 2023)	https://www.kaggle.com/datasets/vbookshelf/rice-leaf-diseases, https://data.mendeley.com/datasets/fwcj7stb8r/1	Bacteria leaf, blight, brown spot, huspa, leaf blast, leaf scalb, leaf streak, narrow brown spot, sheath blight, tungro

(Ritharson et al., 2024)	https://data.mendeley.com/datasets/fwcj7stb8r/draft?a=d8923d0-cfc6-4c6c-adc0-640f10152fdf , UCI & kaggle	Tungro, blast, bacteria blight, brown spot,
(Mahadevan et al., 2024)	https://www.kaggle.com/minhhuy2810/rice-diseases-image-dataset	Bacteria blight, leaf blast, brown spot, tungro
(Mandwariya & Jotwani, 2024)	Manually collected	Healthy, Leaf blast, brown spot, bacteria blight, bacteria leaf blight, false stump, neck blast, stemborer, tungro, hispa, BPH
(Trinh et al., 2024)	Manually Collected	Leaf blast, leaf folder, brown spot

The availability of these datasets has enabled the development of practical tools and applications for rice disease management. For instance, mobile applications leveraging deep learning models trained on datasets like PlantVillage and RHDD are now being used by farmers to identify diseases in real time (Yu & Zheng, 2024b). Drones equipped with cameras and lightweight deep learning models, such as MobileNet and YOLOv5, are being deployed for large-scale monitoring of rice fields(Song et al., 2024). These systems not only detect diseases but also provide actionable insights, such as targeted pesticide application and yield predictions, improving efficiency and reducing costs (Getahun et al., 2024).
IoT-enabled devices integrated with scalable deep learning models are revolutionizing disease detection in resource-constrained environments (Rajaganapathi et al., 2024). For example, edge computing platforms allow real-time analysis of captured images without the need for internet connectivity (Hamdan et al., 2020). This has significant implications for rural farming communities, where technological resources are often not available.

VI. CHALLENGES AND LIMITATIONS

Significant complications arise in rice disease detection as a result of overlapping symptoms. Diseases like bacterial leaf blight, brown spot, and leaf blast often exhibit similarities in visual patterns. Visible disease symptoms seen as spots, discoloration, or lesions, make it very challenging to differentiate between the different categories of diseases. These can lead to misclassification, especially where datasets are inconsistently labeled. Incorrect treatment strategies are a result of misclassification and can affect decision-making processes, which underlines the need for precise diagnosis.

Another noticeable challenge with deep learning-based approaches for disease detection is the problem of overfitting. Limited or unbalanced datasets used to train models often skew such models to memorize specific patterns in the training data, which eventually compromises their ability to make generalization to new or a more diverse dataset. The condition of the environment, the settings of cameras, and the way the diseases are presented can vary significantly which is particularly problematic in the field of agriculture. To mitigate the problem of overfitting, common methods of data augmentation techniques and robust cross-validation are employed by researchers as possible solutions.

Another area of concern is scalability. Field conditions remains a persistent challenge as models developed to work in controlled settings frequently fail to maintain accuracy in real-world applications due to factors such as variations in lighting, background noise, and overlapping leaves. In addition to that, factors such as dust, humidity, and pest interference exacerbate the issue.

VII. FUTURE DIRECTION

Addressing the current limitations and ensuring scalable, efficient, and robust systems will bring about a bright future of rice disease detection and classification using deep learning. A major area of focus should be the development of multi-modal systems that incorporate data from various imaging sources, such as RGB, hyperspectral, and thermal cameras (Kalamkar & A., 2023). These multi-modal frameworks can significantly enhance accuracy by utilizing complementary data modalities to capture both visible and subtle disease markers (S.K.B et al., 2024). This integration can mitigate challenges posed by overlapping symptoms and environmental variations, which often hinder the effectiveness of single-modal approaches (Z. Wang, Wang, et al., 2024).

Building generalizable models capable of performing across diverse field conditions is another critical direction. Domain adaptation techniques, which adjust pre-trained models to new environments, and federated learning, which trains models across decentralized datasets while preserving privacy, can help achieve this (Z. Wang, Yang, et al., 2024). Moreover, advanced data augmentation strategies, such as synthetic data generation and style transfer techniques, can improve model robustness by simulating diverse field scenarios, enabling them to handle real-world variability more effectively (W. Jiang et al., 2024).

Integration with precision agriculture systems is essential for enhancing the practical impact of deep learning-based solutions. These systems can utilize automated drone-based data collection for large-scale monitoring and link with irrigation and pest control mechanisms for precise and targeted interventions (Guebsi et al., 2024). Developing mobile applications that provide real-time disease detection and actionable recommendations to farmers can bridge the gap between advanced technology and end users, ensuring that these systems are user-friendly and accessible (Kamal & Bablu, 2023).

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CONCLUSION

Technological advancement especially in the field of deep learning, have produced algorithms that have demonstrated excellent capability in achieving high accuracy in detecting and classifying rice diseases, offering transformative potentials in the agricultural domain. Be that as it may, challenges such as overlapping symptoms, overfitting, and adapting models to real-world conditions still remain a very big challenge that needs to be addressed. Overcoming these challenges requires robust and scalable model development, wide range datasets, and practical testing in field environments. Going forward, interdisciplinary efforts and real-world implementation will be required as a key to ensuring that these technologies deliver concrete benefits to farmers, advancing agricultural productivity, quality yields and food security.

REFERENCES

[1] Ahad, M. T., Li, Y., Song, B., & Bhuiyan, T. (2023). Comparison of CNN-based deep learning architectures for rice diseases classification. *Artificial Intelligence in Agriculture*, *9*, 22–35. https://doi.org/10.1016/j.aiia.2023.07.001

[2] Ahmed, K., Shahidi, T. R., Irfanul Alam, S. Md., & Momen, S. (2019). Rice Leaf Disease Detection Using Machine Learning Techniques.

2019 International Conference on Sustainable Technologies for Industry 4.0 (STI), 1–5. https://doi.org/10.1109/STI47673.2019.9068096

[3] Andrianto, H., Suhardi, Faizal, A., & Armandika, F. (2020). Smartphone Application for Deep Learning-Based Rice Plant Disease Detection. *2020 International Conference on Information Technology Systems and Innovation (ICITSI)*, 387–392. https://doi.org/10.1109/ICITSI50517.2020.9264942

[4] Bari, B. S., Islam, M. N., Rashid, M., Hasan, M. J., Razman, M. A. M., Musa, R. M., Ab Nasir, A. F., & P.P. Abdul Majeed, A. (2021). A real-time approach of diagnosing rice leaf disease using deep learning-based faster R-CNN framework. *PeerJ Computer Science*, *7*, e432. https://doi.org/10.7717/peerj-cs.432

[5] Bhattacharya, S., Mukherjee, A., & Phadikar, S. (2020). *A Deep Learning Approach for the Classification of Rice Leaf Diseases* (pp. 61–69). https://doi.org/10.1007/978-981-15-2021-1_8

[6] Borawar, L., & Kaur, R. (2023). *ResNet: Solving Vanishing Gradient in Deep Networks* (pp. 235–247). https://doi.org/10.1007/978-981-19-8825-7_21

[7] Cravero, A., Pardo, S., Sepúlveda, S., & Muñoz, L. (2022). Challenges to Use Machine Learning in Agricultural Big Data: A Systematic Literature Review. *Agronomy*, *12*(3), 748. https://doi.org/10.3390/agronomy12030748

[8] Daniya, T., & Vigneshwari, S. (2022). Deep Neural Network for Disease Detection in Rice Plant Using the Texture and Deep Features. *The Computer Journal*, *65*(7), 1812–1825. https://doi.org/10.1093/comjnl/bxab022

[9] Daniya, T., & Vigneshwari, S. (2023). Rice Plant Leaf Disease Detection and Classification Using Optimization Enabled Deep Learning. *Journal of Environmental Informatics*. https://doi.org/10.3808/jei.202300492

[10] Deng, R., Tao, M., Xing, H., Yang, X., Liu, C., Liao, K., & Qi, L. (2021). Automatic Diagnosis of Rice Diseases Using Deep Learning. *Frontiers in Plant Science*, *12*. https://doi.org/10.3389/fpls.2021.701038

[11] Dorairaj, D., & Govender, N. T. (2023). Rice and paddy industry in Malaysia: governance and policies, research trends, technology adoption and resilience. *Frontiers in Sustainable Food Systems*, *7*. https://doi.org/10.3389/fsufs.2023.1093605

[12] Dutta, M., Islam Sujan, M. R., Mojumdar, M. U., Chakraborty, N. R., Marouf, A. Al, Rokne, J. G., & Alhajj, R. (2024). Rice Leaf Disease Classification—A Comparative Approach Using Convolutional Neural Network (CNN), Cascading Autoencoder with Attention Residual U-Net (CAAR-U-Net), and MobileNet-V2 Architectures. *Technologies*, *12*(11), 214. https://doi.org/10.3390/technologies12110214

[13] Getahun, S., Kefale, H., & Gelaye, Y. (2024). Application of Precision Agriculture Technologies for Sustainable Crop Production and Environmental Sustainability: A Systematic Review. *The Scientific World Journal*, *2024*(1). https://doi.org/10.1155/2024/2126734

[14] Guebsi, R., Mami, S., & Chokmani, K. (2024). Drones in Precision Agriculture: A Comprehensive Review of Applications, Technologies, and Challenges. *Drones*, *8*(11), 686. https://doi.org/10.3390/drones8110686

[15] Gülmez, B. (2024). Advancements in rice disease detection through convolutional neural networks: A comprehensive review. *Heliyon*, *10*(12), e33328. https://doi.org/10.1016/j.heliyon.2024.e33328

[16] Hadi, H. P., Rachmawanto, E. H., & Ali, R. R. (2024). Comparison of DenseNet-121 and MobileNet for Coral Reef Classification. *MATRIK : Jurnal Manajemen, Teknik Informatika Dan Rekayasa Komputer*, *23*(2), 333–342. https://doi.org/10.30812/matrik.v23i2.3683

[17] Hamdan, S., Ayyash, M., & Almajali, S. (2020). Edge-Computing Architectures for Internet of Things Applications: A Survey. *Sensors*, *20*(22), 6441. https://doi.org/10.3390/s20226441

[18] Hamhongsa, W., Wiangsripanawan, R., & Thorncharoensri, P. (2023). *Rice Diseases Recognition Using Transfer Learning from Pre-trained CNN Model* (pp. 183–197). https://doi.org/10.1007/978-3-031-30474-3_16

[19] Hasan, Md. J., Mahbub, S., Alom, Md. S., & Abu Nasim, Md. (2019). Rice Disease Identification and Classification by Integrating Support Vector Machine With Deep Convolutional Neural Network. *2019 1st International Conference on Advances in Science, Engineering and Robotics Technology (ICASERT)*, 1–6. https://doi.org/10.1109/ICASERT.2019.8934568

[20] Hassan, S. M., Maji, A. K., Jasiński, M., Leonowicz, Z., & Jasińska, E. (2021). Identification of Plant-Leaf Diseases Using CNN and Transfer-Learning Approach. *Electronics*, *10*(12), 1388. https://doi.org/10.3390/electronics10121388

[21] Jiang, F., Lu, Y., Chen, Y., Cai, D., & Li, G. (2020). Image recognition of four rice leaf diseases based on deep learning and support vector machine. *Computers and Electronics in Agriculture*, *179*, 105824. https://doi.org/10.1016/j.compag.2020.105824

[22] Jiang, W., Zhang, Y., Zheng, S., Liu, S., & Yan, S. (2024). Data augmentation in human-centric vision. *Vicinagearth*, *1*(1), 8. https://doi.org/10.1007/s44336-024-00002-9

[23] John, M. A., Bankole, I., Ajayi-Moses, O., Ijila, T., Jeje, T., & Lalit, P. (2023). Relevance of Advanced Plant Disease Detection Techniques in Disease and Pest Management for Ensuring Food Security and Their Implication: A Review. *American Journal of Plant Sciences*, *14*(11), 1260–1295. https://doi.org/10.4236/ajps.2023.1411086

[24] Kalamkar, S., & A., G. M. (2023). Multimodal image fusion: A systematic review. *Decision Analytics Journal*, *9*, 100327. https://doi.org/10.1016/j.dajour.2023.100327

[25] Kamal, M., & Bablu, T. A. (2023). *Mobile Applications Empowering Smallholder Farmers: An Analysis of the Impact on Agricultural Development*. https://www.researchgate.net/publication/374164307

[26] Kiratiratanapruk, K., Temniranrat, P., Kitvimonrat, A., Sinthupinyo, W., & Patarapuwadol, S. (2020). *Using Deep Learning Techniques to Detect Rice Diseases from Images of Rice Fields* (pp. 225–237). https://doi.org/10.1007/978-3-030-55789-8_20

[27] Mahadevan, K., Punitha, A., & Suresh, J. (2024). Automatic recognition of Rice Plant leaf diseases detection using deep neural network with improved threshold neural network. *E-Prime - Advances in Electrical Engineering, Electronics and Energy*, *8*, 100534. https://doi.org/10.1016/j.prime.2024.100534

[28] Mall, P. K., Singh, P. K., Srivastav, S., Narayan, V., Paprzycki, M., Jaworska, T., & Ganzha, M. (2023). A comprehensive review of deep neural networks for medical image processing: Recent developments and future opportunities. *Healthcare Analytics*, *4*, 100216. https://doi.org/10.1016/j.health.2023.100216

[29] Mandwariya, D., & Jotwani, V. (2024). *A Deep Learning Approach For Automated Rice Disease Detection And Classification*.

[30] Mathew, N. (2024). *Deep Learning for Image Recognition: Enhancing Accuracy and Efficiency with Big Data*. https://doi.org/10.13140/RG.2.2.16387.52004

[31] Mohidem, N. A., Hashim, N., Shamsudin, R., & Che Man, H. (2022). Rice for Food Security: Revisiting Its Production, Diversity, Rice Milling Process and Nutrient Content. *Agriculture*, *12*(6), 741. https://doi.org/10.3390/agriculture12060741

[32] Mumuni, A., & Mumuni, F. (2022). Data augmentation: A comprehensive survey of modern approaches. *Array*, *16*, 100258. https://doi.org/10.1016/j.array.2022.100258

[33] P. Narmadha, R., Sengottaiyan, N., & J. Kavitha, R. (2022). Deep Transfer Learning Based Rice Plant Disease Detection Model. *Intelligent Automation & Soft Computing*, *31*(2), 1257–1271. https://doi.org/10.32604/iasc.2022.020679

[34] Patidar, S., Pandey, A., Shirish, B. A., & Sriram, A. (2020). *Rice Plant Disease Detection and Classification Using Deep Residual Learning* (pp. 278–293). https://doi.org/10.1007/978-981-15-6315-7_23

[35] Phung, V. H., & Rhee, E. J. (2019). A High-Accuracy Model Average Ensemble of Convolutional Neural Networks for Classification of Cloud Image Patches on Small

Datasets. *Applied Sciences*, *9*(21), 4500. https://doi.org/10.3390/app9214500

[36] Prajapati, H. B., Shah, J. P., & Dabhi, V. K. (2017). Detection and classification of rice plant diseases. *Intelligent Decision Technologies*, *11*(3), 357–373. https://doi.org/10.3233/IDT-170301

[37] Rajaganapathi, R., Mahendran, R., Sivaganesan, D., Vadivel, Mr. R., Joel, M. R., & Kannan, V. (2024). An IoT enabled computational model and application development for monitoring cardiovascular risks. *E-Prime - Advances in Electrical Engineering, Electronics and Energy*, *8*, 100513. https://doi.org/10.1016/j.prime.2024.100513

[38] Ramesh, S., & Vydeki, D. (2018). Rice Blast Disease Detection and Classification Using Machine Learning Algorithm. *2018 2nd International Conference on Micro-Electronics and Telecommunication Engineering (ICMETE)*, 255–259. https://doi.org/10.1109/ICMETE.2018.00063

[39] Ritharson, P. I., Raimond, K., Mary, X. A., Robert, J. E., & J, A. (2024). DeepRice: A deep learning and deep feature based classification of Rice leaf disease subtypes. *Artificial Intelligence in Agriculture*, *11*, 34–49. https://doi.org/10.1016/j.aiia.2023.11.001

[40] Saxena, S., Shukla, S., & Gyanchandani, M. (2020). Pre-trained convolutional neural networks as feature extractors for diagnosis of breast cancer using histopathology. *International Journal of Imaging Systems and Technology*, *30*(3), 577–591. https://doi.org/10.1002/ima.22399

[41] Senapati, M., Tiwari, A., Sharma, N., Chandra, P., Bashyal, B. M., Ellur, R. K., Bhowmick, P. K., Bollinedi, H., Vinod, K. K., Singh, A. K., & Krishnan, S. G. (2022). Rhizoctonia solani Kühn Pathophysiology: Status and Prospects of Sheath Blight Disease Management in Rice. *Frontiers in Plant Science*, *13*. https://doi.org/10.3389/fpls.2022.881116

[42] Sethy, P. K., Barpanda, N. K., Rath, A. K., & Behera, S. K. (2020). Deep feature based rice leaf disease identification using support vector machine. *Computers and Electronics in Agriculture*, *175*, 105527. https://doi.org/10.1016/j.compag.2020.105527

[43] Shamsuzzaman, M. (2022). Transfer Learning based Approach to Crops Leaf Disease Detection: A Diversion Changer in Agriculture. *Article in International Journal of Engineering Research*. https://doi.org/10.17577/IJERTV11IS090062

[44] Shoaib, M., Shah, B., EI-Sappagh, S., Ali, A., Ullah, A., Alenezi, F., Gechev, T., Hussain, T., & Ali, F. (2023). An advanced deep learning models-based plant disease detection: A review of recent research. *Frontiers in Plant Science*, *14*. https://doi.org/10.3389/fpls.2023.1158933

[45] Shrivastava, V. K., & Pradhan, M. K. (2021). Rice plant disease classification using color features: a machine learning paradigm. *Journal of Plant Pathology*, *103*(1), 17–26. https://doi.org/10.1007/s42161-020-00683-3

[46] Shrivastava, V. K., Pradhan, M. K., Minz, S., & Thakur, M. P. (2019). RICE PLANT DISEASE CLASSIFICATION USING TRANSFER LEARNING OF DEEP CONVOLUTION NEURAL NETWORK. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XLII-3/W6*, 631–635. https://doi.org/10.5194/isprs-archives-XLII-3-W6-631-2019

[47] Simhadri, C. G., & Kondaveeti, H. K. (2023). Automatic Recognition of Rice Leaf Diseases Using Transfer Learning. *Agronomy*, *13*(4), 961. https://doi.org/10.3390/agronomy13040961

[48] Simhadri, C. G., Kondaveeti, H. K., Vatsavayi, V. K., Mitra, A., & Ananthachari, P. (2024a). Deep learning for rice leaf disease detection: A systematic literature review on emerging trends, methodologies and techniques. *Information Processing in Agriculture*. https://doi.org/10.1016/j.inpa.2024.04.006

[49] Simhadri, C. G., Kondaveeti, H. K., Vatsavayi, V. K., Mitra, A., & Ananthachari, P. (2024b). Deep learning for rice leaf disease detection: A systematic literature review on emerging trends, methodologies and techniques. *Information Processing in Agriculture*. https://doi.org/10.1016/j.inpa.2024.04.006

[50] Singla, P., Niharika, jain, R., Sharma, R., Kukreja, V., & Bansal, A. (2022). Deep Learning Based Multi-Classification Model for Rice Disease Detection. *2022 10th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO)*, 1–5. https://doi.org/10.1109/ICRITO56286.2022.9965117

[51] S.K.B, S., Mathivanan, S. K., Karthikeyan, P., Rajadurai, H., Shivahare, B. D., Mallik, S., & Qin, H. (2024). An enhanced multimodal fusion deep learning neural network for lung cancer classification. *Systems and Soft Computing*, *6*, 200068. https://doi.org/10.1016/j.sasc.2023.200068

[52] Song, Z., Ban, S., Hu, D., Xu, M., Yuan, T., Zheng, X., Sun, H., Zhou, S., Tian, M., & Li, L. (2024). A Lightweight YOLO Model for Rice Panicle Detection in Fields Based on UAV Aerial Images. *Drones*, *9*(1), 1. https://doi.org/10.3390/drones9010001

[53] Sutaji, D., & Rosyid, H. (2022). Convolutional Neural Network (CNN) Models for Crop Diseases Classification. *Kinetik: Game Technology, Information System, Computer Network, Computing, Electronics, and Control*. https://doi.org/10.22219/kinetik.v7i2.1443

[54] Trinh, D. C., Mac, A. T., Dang, K. G., Nguyen, H. T., Nguyen, H. T., & Bui, T. D. (2024). Alpha-EIOU-YOLOv8: An Improved Algorithm for Rice Leaf Disease Detection. *AgriEngineering*, *6*(1), 302–317. https://doi.org/10.3390/agriengineering6010018

[55] Upadhyay, S. K., & Kumar, A. (2022). A novel approach for rice plant diseases classification with deep convolutional neural network. *International Journal of Information Technology*, *14*(1), 185–199. https://doi.org/10.1007/s41870-021-00817-5

[56] V, S., Bhagwat, A., & Laxmi, V. (2024). LeafSpotNet: A deep learning framework for detecting leaf spot disease in jasmine plants. *Artificial Intelligence in Agriculture*, *12*, 1–18. https://doi.org/10.1016/j.aiia.2024.02.002

[57] Venu Vasantha, S., Samreen, S., & Lakshmi Aparna, Y. (2022). Rice Disease Diagnosis System (RDDS). *Computers, Materials & Continua*, *73*(1), 1895–1914. https://doi.org/10.32604/cmc.2022.028504

[58] Wang, Y., Wang, H., & Peng, Z. (2021). Rice diseases detection and classification using attention based neural network and bayesian optimization. *Expert Systems with Applications*, *178*, 114770. https://doi.org/10.1016/j.eswa.2021.114770

[59] Wang, Z., Wang, T., Zhang, X., Wang, J., Yang, Y., Sun, Y., Guo, X., Wu, Q., Nepovimova, E., Watson, A. E., & Kuca, K. (2024). Biodiversity conservation in the context of climate change: Facing challenges and management strategies. *Science of The Total Environment*, *937*, 173377. https://doi.org/10.1016/j.scitotenv.2024.173377

[60] Wang, Z., Yang, G., Dai, H., & Bai, Y. (2024). DAFL: Domain adaptation-based federated learning for privacy-preserving biometric recognition. *Future Generation Computer Systems*, *150*, 436–450. https://doi.org/10.1016/j.future.2023.09.020

[61] Wani, J. A., Sharma, S., Muzamil, M., Ahmed, S., Sharma, S., & Singh, S. (2022). Machine Learning and Deep Learning Based Computational Techniques in Automatic Agricultural Diseases Detection: Methodologies, Applications, and Challenges. *Archives of Computational Methods in Engineering*, *29*(1), 641–677. https://doi.org/10.1007/s11831-021-09588-5

[62] Yadav, R., Azad, C. S., Kumar, R., Kumar, U., & Patel, S. V. (2023). TECHNOLOGICAL ADVANCEMENTS DRIVING AGRICULTURAL TRANSFORMATION. *AgriSustain AgriSustain-An International Journal*, *2023*(2), 5–11. https://doi.org/10.5281/zenedo.8385249

[63] Yu, X., & Zheng, J. (2024a). A Review on the Application of Deep Learning Methods in Detection and Identification of Rice Diseases and Pests. *Computers, Materials & Continua*, *78*(1), 197–225. https://doi.org/10.32604/cmc.2023.043943

[64] Yu, X., & Zheng, J. (2024b). A Review on the Application of Deep Learning Methods in Detection and Identification of Rice Diseases and

Pests. *Computers, Materials & Continua*, *78*(1), 197–225. https://doi.org/10.32604/cmc.2023.043943

[65] Yusuf, H. M., Yusuf, S. A., Abubakar, A. H., Abdullahi, M., & Hassan, I. H. (2024). A systematic review of deep learning techniques for rice disease recognition: Current trends and future directions. *Franklin Open*, *8*, 100154. https://doi.org/10.1016/j.fraope.2024.100154