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"Advanced Techniques For Rice Disease Detection: A Comprehensive Review"

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Abstract *–*
A very important part of making sure food is safe around the world is rice, which is one of the most important main crops. Rice plants can get a lot of different diseases, and any one of them can severely lower the yield or grade of the crop. Early diagnosis of these disorders and proper classification are both important for the best management of these diseases. This review paper offers a comprehensive overview of recent advancements in rice disease detection methods, with a particular focus on the application of machine learning and deep learning techniques. The primary objective is to provide a consolidated summary of research findings, methodologies, and technological developments in the field of rice disease detection. The paper begins by emphasizing the global significance of rice as a food source and the detrimental effects of diseases on rice production. It highlights the limitations of traditional disease detection methods, such as manual inspection, and the need for more efficient and precise techniques. The review extensively covers a wide range of studies and approaches employed for rice disease detection. It shows how to use different machine learning methods, like decision trees, convolutional neural networks (CNNs), support vector machines (SVMs), and k-Nearest Neighbours (k-NN), to automatically find diseases in rice plants. The paper discusses the benefits of using these algorithms for image-based classification of healthy and diseased rice plants. Notably, the review underscores the effectiveness of transfer learning and the use of pre-trained CNN models in achieving high accuracy rates in disease diagnosis. The significance of data augmentation, regularization techniques, and other strategies for enhancing the performance of machine learning models in detecting rice diseases is examined. Several studies have demonstrated the impact of these techniques in increasing the robustness and accuracy of models, making them suitable for real-world agricultural applications.

Keywords: *Machine learning, Rice Disease, CNN, Feature Extraction, Segmentation*

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I. INTRODUCTION

Crop diseases and insect pests have always been big problems for farmers, hurting both the quality and speed of their work and putting the environment at risk.The Food and Agriculture Organisation of the United Nations (FAO) says that thirty percent of the world's total food production is lost every year because of pests and diseases that affect grains[1].The number of agricultural illnesses has gone up because natural events and unexpected weather are happening more often [2].People have done things that have directly caused this to happen, which has warmed the Earth's atmosphere. Climate change has had a big effect on the world economy, food security, and agricultural output.This has made it much harder to keep track of diseases and pests and keep them from spreading. One of the three most important foods in China is rice. It is also one of the three most important grain crops grown around the world. More than sixty-five percent of Chinese people eat rice every day, and the land used for planting rice makes up about a fifth of the country's arable land [3]. New numbers [4] show that there are already about 600 different types of diseases and pests that can affect rice. In China, the main rice pests are the rice planthopper (Sogatella furcifera), the rice leaf borer (Cnaphalocrocis medinalis), and the stem borers (Chilo suppressalis). Magnaporthe oryzae causes rice blast, Rhizoctonia solani Kuhn causes sheath blight, and Rice tungro bacilliform virus causes rice fake smut. These are the main rice diseases in China. Changes in the weather, planting trends, and the environment over the past few years have caused China to lose about 5–6 million tonnes of rice, which has put the country's ability to provide for its own food security at great risk [5].

Figure 1 shows pictures of different diseases and pests that often affect rice. Food security is a big problem that affects the growth of the economy, the safety of society, and the independence of the country. Also, having enough food is a key part of keeping the country safe [6]. The number of people living in the world is expected to reach 9.8 billion by 2050. In order to keep up with the rising demand caused by a growing world population; food production is growing at an amazing rate. But there is only so much land and water to go around, and climate change is making extreme events happen more often. All of these things pose a major threat to the goal of sustainable agriculture.

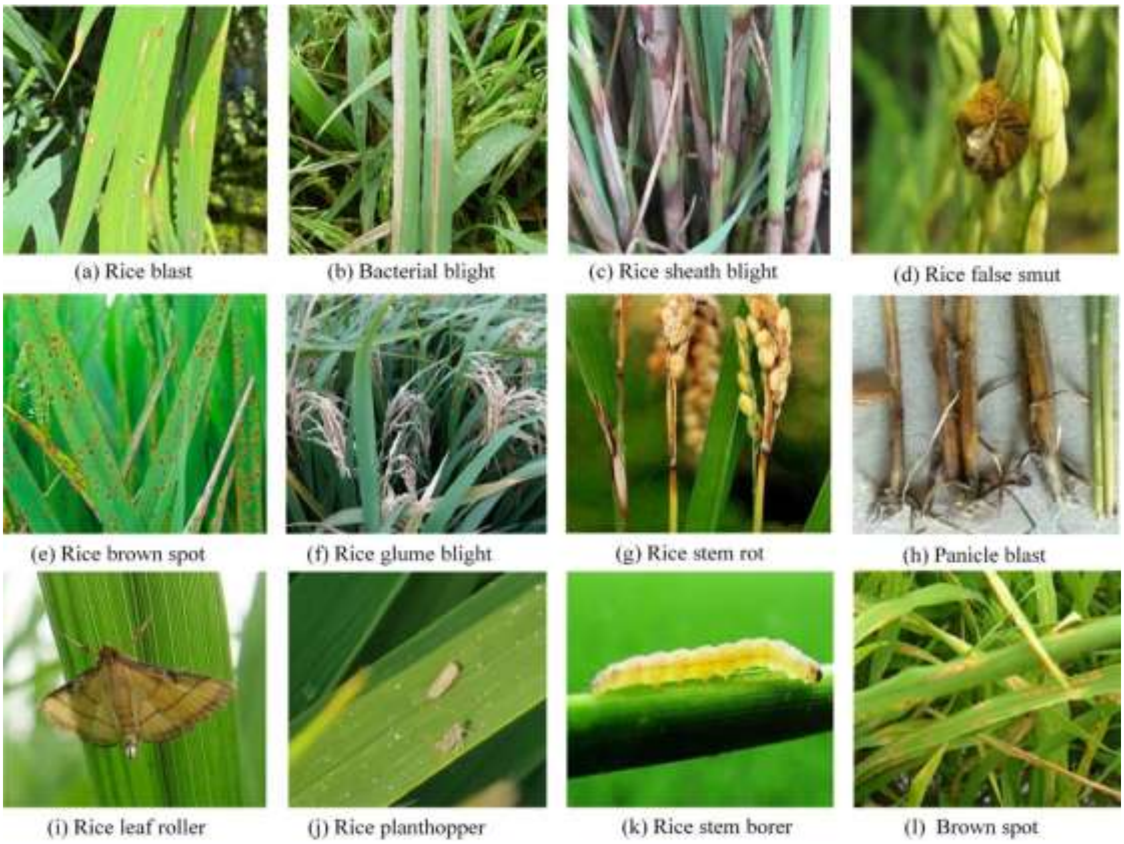

Fig.1 different types of rice disease

The UN has set 14 Sustainable Development Goals (SDGs), and one of them is to ensure food security. Because of the problems that are being faced right now. It is important to keep an eye on and successfully stop rice diseases and pests in order to not only make sure that the quality and yield of rice are good, but also to protect the safety of more than a billion people. In the past, trained plant protection experts' investigations and assessments in the field have been the main ways that rice diseases and pests were tracked. This method has been used for a long time, but it's only good for small amounts of study, and the results are hard to understand, take a long time, and can be interpreted in different ways [7]. With these old-fashioned methods, it's hard to deal with disease or pest control situations that are getting more complicated; it's hard to stop problems like the spread of disease and disasters. Such field studies can't meet the needs that need to be met in real time and in a changing way in order to keep an eye on rice diseases and pests on a large scale.

Remote sensing is becoming more popular for keeping an eye on farming diseases and pests [8]. Since it is the only tool that can quickly gather surface data that is continuous across a large area, this is the case. As of not long ago, the Chinese Ministry of Agriculture and Rural Affairs released the Digital Agriculture Rural Development Plan (2019–2025). It was very clear from this plan that one of the best ways to get rid of pests is to use remote sensing to keep an eye on diseases and pests that hurt important crops and send out early alerts.With the fast growth of space technology over the past few years, remote sensing data sources have become more varied. This can be seen in the rise of aerial images. We are seeing more and more of different types of data sources on board and in the air. A number of these are high-resolution Earth observation satellites from China (GF series), new satellites from the European Space Agency (Sentinel-1 and Sentinel-2 series), and unmanned aerial vehicles that collect hyper spectral and multispectral remote sensing data. In April and May of this year, China launched the Sentinel-1 and Sentinel-2 sets of satellites. The GF series is one of China's high-resolution Earth observation satellites that watch the Earth from space. Each of these data sources provides information from remote sensing that has a range of different temporal, geographical, and spectral resolutions that can be used to keep an eye on crop diseases and pests.[9]

Different Types of Rice Plant Diseases

Rice, one of the world's most important staple crops, is susceptible to a variety of diseases that can reduce crop yields and quality. These diseases are caused by various pathogens, including fungi, bacteria, viruses, and nematodes. Here are some common types of rice plant diseases:

Blast (Magnaporthe oryzae): Blast is one of the most destructive rice diseases. It affects all parts of the plant, including leaves, stems, and grains. Symptoms include small, water-soaked lesions that turn into brown or grayish spots with a white center. The disease can lead to severe yield losses.

Brown Spot (Cochliobolus miyabeanus): Brown spot is a fungal disease that causes small, dark brown lesions with a yellow halo on rice leaves. Severe infections can lead to reduced photosynthesis and yield loss.

Sheath Blight (Rhizoctonia solani): Sheath blight is a fungal disease that affects the sheaths and blades of rice leaves, causing elongated lesions that can girdle and kill the plant. It can be a significant problem in regions with high humidity and moderate temperatures.

Bacterial Leaf Blight (Xanthomonas oryzae pv. oryzae): This is a bacterial disease that affects rice leaves, causing water-soaked lesions that turn brown and eventually wither. It can result in significant yield losses.

Tungro Disease: Tungro is a viral disease transmitted by green leafhoppers. It is caused by a complex of two viruses, Rice Tungro Bacilliform Virus (RTBV) and Rice Tungro Spherical Virus (RTSV). Infected plants exhibit stunted growth, reduced tillering, and yellowing of leaves.

Rice Yellow Mottle Virus (RYMV): RYMV is a viral disease that causes yellowing of rice leaves and can lead to yield losses in susceptible rice varieties. It is transmitted by planthoppers.

Rice Grassy Stunt (RGS) and Rice Ragged Stunt (RRS): These are two diseases caused by phytoplasmas, which are microscopic bacteria-like pathogens. RGS and RRS cause stunted growth, leaf yellowing, and reduced yield in infected rice plants.

False Smut (Ustilaginoidea virens): False smut is a fungal disease that affects rice grains. Infected grains form large, greenish spore balls that resemble smut balls. This disease can reduce grain quality and yield.

Kernel Smut (Tilletia barclayana): Kernel smut is a fungal disease that infects rice grains, leading to the formation of dark, powdery masses within the grain. It reduces grain quality and market value.

Root-Knot Nematodes (Meloidogyne spp.): Root-knot nematodes are microscopic roundworms that parasitize the roots of rice plants, causing the formation of characteristic galls or knots on the roots. They can lead to reduced nutrient and water uptake, resulting in stunted growth**.[10]**

Table 1. Classification of various rice diseases with symptoms

Disease Stage Symptoms Important Season Factors for Infection	Disease Stage Symptoms Important Season Factors for Infection	Disease Stage Symptoms Important Season Factors for Infection	Disease Stage Symptoms Important Season Factors for Infection	Disease Stage Symptoms Important Season Factors for Infection
Blast	Bacterial Blight	At flowering to maturity	Rain shower and cooled temperature	High humidity and nitrogen level
Sheath Blight	Bacterial Blight	Greenish grey irregular spot between water and leaf blade	Rainy season	High humidity and nitrogen level
False Smut	At flowering to maturity	Follicles are in orange and at maturity turn greenish yellow or black	In periodic rain fall	Extreme nitrogen and high humidity
Brown Spot	Flowering to maturity	Brown to purple-brown oval spot on leaves	Periodic rain	High humidity, soil deficiency and high temperature
Bacterial Blight	Tillering to heading	Tan-greyish to white	In wet	High temperature and humidity

II. RESEARCH METHODOLOGY

the systematic review is well-structured and follows the standard procedures for conducting a literature review in the field of computer vision, artificial intelligence, and deep learning for rice disease detection. Here are some key points and considerations based on methodology:

Data Collection:

Choice of databases (Science Direct, Scopus, Springer, ACM, and IEEE) is appropriate as these sources cover a wide range of relevant research papers.The time interval from 2014 to 2023 is reasonable for collecting recent research.

Search Terms:

The search expression is well-constructed and includes various relevant terms, ensuring a comprehensive search for papers related to rice disease using computer vision and AI/ML/DL techniques

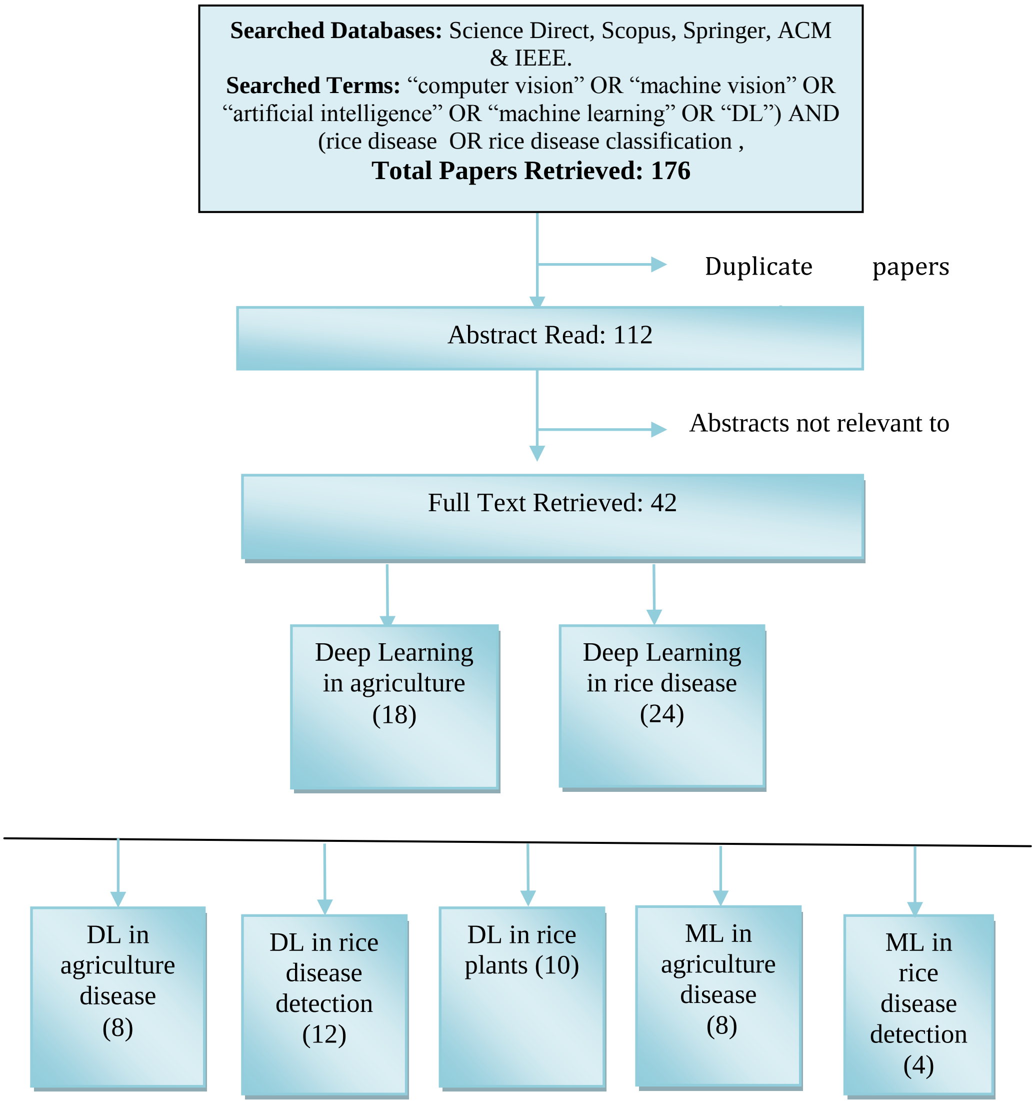

Fig 1: Research Methodology Flow

Inclusion Criteria:

Titles and abstracts are often the first step in screening papers for relevancy, removing duplicate papers is a necessary step to ensure the uniqueness of the papers selected for review.

Exclusion Criteria:

Excluding papers that do not specifically deal with rice disease detection and diagnosis using deep learning is a valid criterion, to focus on papers directly related to research topic.

Data Analysis:

Categorizing the selected papers based on the points mentioned will help in organizing and presenting findings clearly.

Year of Publication:

Analyzing the publication years can provide insights into the evolution and increasing interest in deep learning for rice disease.

Purpose of the Study:

Understanding the different purposes of the studies (lesion detection, classification, segmentation, etc.) is essential for assessing the versatility of deep learning in rice disease.

Image Acquisition Technique:

It's crucial to identify the imaging techniques used, as different cancers may require different imaging modalities for accurate detection.

Deep Learning Architecture:

Recognizing the specific deep learning architectures employed in the selected papers will demonstrate the diversity of approaches in this field.

Training Method:

Distinguishing between end-to-end training and transfer learning is valuable, as it showcases the variety of training methods used in rice disease applications.

Image Dataset:

The type and size of image datasets used in the studies can indicate the feasibility and effectiveness of the proposed systems, especially in deep learning, where large datasets are often essential..

III. LITERATURE REVIEW

New Research Says Machine learning algorithms play a big role in putting images into the right groups based on traits they have in common. Image processing is one of the main parts of these algorithms. 2022, 11, and 2230 are common plant names for machine learning methods. It has three steps: preprocessing, feature extraction, and classification. Depending on how they work, classifiers can be either supervised or unsupervised methods. In recent years, there has been a huge increase in the use of DL algorithms in research. DL algorithms are given proposed photos and are used to extract features and classify images. There are many types of study problems that can be solved with both machine learning and deep learning algorithms. In the areas of education [11], health care [12], smart cities [13], and any other area that touches people. The ultimate goal is to assign tasks that people usually do to machines, which will have the extra benefit of being done by machines. This piece talks about three diseases that affect rice crops: brown spots, false smuts, and bacterial leaf blight. The authors suggest using Support Vector Machines (SVM) to sort the diseases into groups. They recommended using the Scale-Invariant feature transform (SIFT) and the Bag of Words (BoW) to pull out features. Also, they recommended using the K-means clustering method along with the Brute-Force (BF) matcher and then SVM for classification. They used a set of 400 photos that they got from different places, like the American Psychopathological Society (APS), the Rice Knowledge Bank (RKB), and the Rice Research Institute (RRI).

The average rate of accuracy was 94.16 percent, the average rate of memory was 91.6 percent, and the average rate of precision was 90.9 percent. They did have a very small sample, which is a problem when showing multiclass classification because SVM is a classifier that tends to overfit. Especially when thinking about grouping into more than one class.

The writers of the study [14] suggest deep convolutional neural networks (CNNs) as a way to find out if someone has rice blast disease. The sample they used had 5812 rice plants, with an equal number of infected and non-infected plants. The people can use this dataset. They said that their method, which uses CNN to fetch features and SVM to classify them, was 95.63% accurate when used for binary classification. As a way to find and stop rice diseases, image processing is proposed in the article [15]. The main diseases they are after are rice sheath disease, rice brown spot disease, rice blast disease, and rice bacterial blight disease. They say that engineered parts should be used that are based on the object's shape and colour. Traditional classifiers like k-Nearest Neighbour (k-NN) and Minimum Distance Classifier (MDC) are two that they suggest using in the classification process. In order to study these disorders, they used a dataset with only 115 photos, which was split into a 30% testing part and a 70% training portion. They said that k-NN was 87.02% accurate overall, while MDC was 89.23% accurate. Their sample is too small to be used for multiclass classification, and they don't talk about over fitting in their work.

The writers of [16] suggest that machine learning methods could be used to treat rice leaf disease. The three main types of rice leaf illnesses that they treat are bacterial leaf blight, leaf smut, and brown spot. With 120 pictures spread out equally across the three disorders, the dataset shown in [17] is used. Researchers advised using traditional classifiers like Decision Tree (DT), Logistic Regression (LR), Naive Bayes (NB), J48 DT, and K-nearest neighbour (K-NN) for the procedure of classification. When they used the J48 DT, they found that it was 97.9% accurate. This result is not a surprise because the dataset was not very big. The authors of the study [18] suggest using k-mean clustering to separate the sick part of the leaf and then getting features from the infected area based on its texture, shape, and colour. They said the SVM they used was accurate 93.33% of the time on the training data but only 73.33% of the time on the testing data.

In , the writers group diseases that affect rice plants into groups based on the colours of their symptoms. After looking at 14 different colour spaces, they came up with 172 features by taking four colour traits from each channel. For their study, they used a dataset with 619 pictures split into four groups: rice blast, bacterial leaf blight, healthy leaves, and sheath blight. After that, they tested their method using seven different models, such as the K-NN classifier, the support vector machine (SVM), the logistic regression, and the random forest (RF). With an average accuracy of 94.65%, they found that using SVM gave them the best results. There is a full analysis of AI and ML methods for diagnosing rice diseases in [19].

Photographs have been used in a number of different ways to correctly ID plant diseases. It's hard for us to learn more because most of them use general image processing methods like SVM classifiers, K-mean grouping, genetic algorithms, and so on. Neural network-based methods are being used by more and more researchers in this area over the past few years. When it comes to using photos to diagnose diseases, deep neural networks are much better than traditional image processing methods. [20]

Varun Pramod Bhartiya et al. 2022: This study discusses using machine learning techniques, particularly the Quadratic SVM algorithm, to diagnose different diseases in rice leaves. They achieved an accuracy of 81.8% and used various features, including shape traits, to distinguish between different rice diseases [21].

B. Siddarajamma et al. 2022: The study focuses on diagnosing rice blast disease, which is caused by a fungus. They used grayscale images and the k-means method to isolate the diseased parts of rice plants, and Support Vector Machine (SVM) for disease classification. Their method achieved a high accuracy of 96.77% [22].

Kalyan Kumar et al. 2021: This research uses a variety of machine learning algorithms, including k-Nearest Neighbor, neural network, SVM, decision tree, random forest, Logistic Regression, AdaBoost, and Naive Bayes, to classify different rice conditions, such as Brown Spot, Hispa, and Leaf Blast. They used Classification Accuracy (CA) as the performance measure [23].

Seksan Mathulaprangsan et al. 2020: The study is conducted in Bangladesh, a major rice-producing country. It uses edge computing and the Raspberry Pi platform to find and classify diseases on rice leaves, focusing on diseases like brown spot, hispa, and leaf blast. They achieved an accuracy grade of 97.50% using the Random Forest algorithm [24].

Gina L et al. 2022: This study is carried out in Thailand and combines image data of rice diseases with deep learning models like ResNets and DenseNet to classify the diseases. The results show an average accuracy of more than 95%, making it a potential tool for Thai farmers [25].

Heri Andrianto et al. 2020: The study investigates how rice leaf samples infected with tungro absorb infrared and visible light. They use machine learning methods, such as artificial neural networks (ANN) and support vector machines (SVM), to find rice tungro infection with high accuracy [26].

Mehwish Moiz et al. 2022: This study leverages deep learning techniques, including VGG 16, and Light GBM to create an architecture for group learning for rice leaf disease classification [27].

Felix Pherry et al. 2022: The research focuses on identifying and classifying the five most common diseases that affect rice leaves: bacterial leaf blight, sheath blight, bacterial leaf blast, brown spot, and tungro. They combine statistical and textural features to achieve a 92.77% accuracy rate [28].

Amandeep Kaur et al. 2022: The study focuses on using deep learning techniques and transfer learning with CNN models (InceptionV3, DenseNet201, and Efficient Net V2S) to diagnose five common diseases of rice leaves. The DenseNet201 model achieved the highest accuracy at 92.05% [29].

Rakesh Meena et al. 2022: The study proposes an image-based machine learning method to differentiate between healthy and diseased Oryza Sativa plants. Various models like VGG16, VGG19, ResNet50, and InceptionV3 were used. The VGG19 model with regularization achieved an accuracy of 84.4% [30].

Syed Taha Yeasin Ramadan et al. 2022: The research explores the use of deep learning methods, particularly Deep Convolutional Neural Networks, to identify and classify different diseases affecting rice plants. The proposed method can distinguish between six disease groups with an accuracy of 97% [31].

Rayner Alfred et al. 2021: The study utilizes thermal images of rice leaves and statistical features, focusing on feature selection with the Puzzle Optimization Algorithm. Various classifiers were tested, with the very randomized trees classifier showing the best performance with a weighted feature selection method [32].

Sudarshan S. Chawathe et al. 2020: The research addresses the challenge of limited images of diseased rice leaves by using Generative Adversarial Networks (GANs) to augment the dataset. It also employs DenseNet121, DenseNet169, MobileNetV2, and VGG16 for disease classification, with the best accuracy achieved by a newly augmented dataset [33].

G.K.V.L Udayananda et al. 2022: This study discusses the impact of Big Data, Machine Learning, and the Internet of Things (IoT) on smart farming, especially in the context of rice production. It emphasizes the importance of efficiently integrating these technologies to improve various aspects of rice farming [34].

Raja Krishna Vamsee Kongara et al. 2022: The research explores rice-specific precision agriculture using Convolutional Neural Networks. It focuses on identifying more than thirty different diseases that can affect paddy fields. InceptionV3 achieved the highest accuracy at 91.23% [35].

V.Jotwani et al.2022: This study aims in which Image classification divides a picture into numerous distinct segments depending on the picture's parametric features. There are currently several assorted strategies of appearing photo segmentation, ranging from the simple threshold approach to the better technique of segmentation of shadow photographs. There are countless and diverse ways to partition photographs, but machines cannot identify things. The image is segmented based on several characteristics. These attributes include color information, border values, and a piece of a picture [36].

V. Rekha et al. 2023: This study targets early detection of eight important diseases that affect rice using a model based on a Raspberry Pi3B+ and various sensors. The model achieved an accuracy rate of 99.7% and sends relevant data to the cloud [37]. Table 2 presents a study of the classification accuracy of the most recent studies on rice diseases.

Table 2. Related Literature Survey to Classify and identify rice leaf diseases.

Study & Year	Objective	Algorithm/Method	Leaf Diseases	Performance
Latif et al. [37] & 2022	Proposed method for identifying and categorizing rice leaf diseases utilizing transfer learning through DCNN.	Modified VGG19	Healthy, Narrow Brown Spot, Leaf Scald, Leaf Blast, Brown Spot, BL	Avg Accuracy96.08% Precision = 96.20% F1-score = 96.16%
Daniya et al. [38] & 2022	Introduced an effective optimization deep learning framework ExpRHGSO algorithm for disease detection and classification	ExpRHGSO Algorithm	Bacterial Leaf Blight, Blast, and Brown spot	Accuracy = 91.6%, Sensitivity = 92.3%, Specificity = 91.9%
Bari et al. [39] & 2021	Faster R-CNN algorithm proposed RPN architecture	Faster R-CNN	Rice blast, Brown spot, and Hispa	Rice blast = 98.09%, Brown Spot = 98.85%, Hispa = 99.17%
Islam et al. [40] & 2021	Proposed an automated detection approach with the deep learning CNNmodel	VGG-19, InceptionResnet V2, ResNet-101, Xception	Brown Spot, Leaf Blight, Leaf Smut, Bacterial Leaf Blast	Accuracy = 92.68% (Inception-ResNet-V2)
Wang et al. [41] & 2021	Proposed the ADSNN-BO model based on MobileNet structure and augmented attention mechanism.	ADSNN-OB model	Brown spot, hispa, and leaf blast.	Accuracy = 94.64
Rahman et al. [42] & 2020	Three different training methods compared on state-of-the-art CNN architectures	VGG16, InceptionV3, MobileNetv2, NasNetMobile, SqueezeNet, SimpleCNN	False Smut, BPH, BLB, Neck Blast, Stemborer, Hispa, Sheath Blight, Brown Spot	VGG16 = 97.12%, InceptionV3 = 96.37%, MobileNetv2 = 96.12%, NasNetMobile = 96.95%, SqueezeNet = 92.5%, Simple CNN = 94.33%

IV. CONCLUSION

In conclusion, the application of machine learning and deep learning techniques for rice disease detection represents a pivotal advancement in agricultural science. The significance of rice as a global food source, combined with the increasing threats posed by diseases and pests, necessitates innovative and efficient solutions for early detection and management. Traditional disease detection methods, such as manual inspection, have limitations in terms of accuracy and scalability, making them inadequate for addressing the challenges posed by an ever-growing world population and changing environmental conditions.

Machine learning algorithms, including decision trees, support vector machines, k-Nearest Neighbors, and, notably, convolutional neural networks (CNNs), have demonstrated their prowess in automatically identifying and classifying rice diseases. By leveraging image-based classification, these methods empower farmers and agricultural experts to swiftly and accurately diagnose plant health, enabling timely intervention to mitigate yield losses.

Furthermore, transfer learning, the use of pre-trained CNN models, data augmentation, and regularization techniques have substantially enhanced the robustness and accuracy of disease detection models. These advances have made machine learning applications for rice disease detection suitable for real-world agricultural settings. As a result, the agricultural sector stands to benefit immensely from the incorporation of these cutting-edge technologies.

In essence, the convergence of machine learning and deep learning methodologies has opened new horizons for sustainable agriculture. The development of precise, efficient, and scalable disease detection systems offers a ray of hope in the face of growing food security concerns, climate-induced challenges, and the ever-increasing global demand for rice. By harnessing the power of these technologies, we are taking proactive steps to ensure that rice, a fundamental crop in our global food supply, can continue to thrive and meet the needs of a burgeoning world population.

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