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Identification of Diseases in Rice Plant Using Machine Learning and Deep Learning

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Abstract
Rice is one of the primary staple foods globally, contributing significantly to the sustenance of millions. However, rice production faces substantial challenges due to various diseases that afflict the crop, leading to yield losses and economic repercussions. Effective farming strategies depend on the early detection and precise identification of these disorders. The nine most significant diseases that affect rice plants such as rice yellow mottle virus, rice blast, brown spot, sheath blight, sheath rot, leaf scald, false smut, kernel smut and grain rot are examined in this survey. Machine learning and deep learning algorithms have been favored for identifying certain disorders, and they have been compared using various factors.
Keywords: Rice diseases, Machine learning, Deep learning, Neural networks.

1. INTRODUCTION
A large section of the world's population, especially in Asia, Africa, and Latin America, depends on rice (Oryza sativa L.), a crucial cereal crop. Its cultivationsustains livelihoods and provides essential nutrition to millions worldwide. However, a number of biotic and abiotic factors have a substantial impact on rice production and yield, with illnesses being one of the main causes of yield losses. Diseases in rice plants, caused bypathogens such as fungi, bacteria, viruses, and nematodes, pose a constant threat to agricultural production. Among the common rice diseases include sheath blight (caused by Rhizoctonia solani), bacterial leaf blight (produced by Xanthomonas oryzae pv. oryzae), and blast (caused by the fungus Magnaporthe oryzae). These illnesses not only lower grain yields but also cause grain quality to decline, which costs farmers money and compromises global food security. Conventional disease diagnosis techniques mostly rely on visual examination conducted by qualified plant pathologists or agronomists. But these procedures are frequently labor-intensive, time-consuming, and prone to human error. Additionally, the expertise required for accurate disease identification may not be readily available in remote or resource-constrained agricultural regions.
The sections mentioned in this paper are as follows. Section II deal with literature survey, section III explains the types of diseases present in the rice plants, section IV demonstrates the methodologies involved in detection of diseases in rice plants, section V illustrates the different intelligent techniques are used, section VI represents hardware and software specifications being implemented and finally section VII provides the performance analysis about the result.

2. LITERATURE SURVEY
In 2023, [2] Yuan Yang et al. identified the diseases in rice plant usinglightweight DGLNet. In the proposed method, recognition accuracy on two real plant disease datasets is achieved 99.82% and 99.71% respectively. In 2023, Kirti et al. [3] proposed Residual-Attention Learning Network to identify plant diseases and produces cutting-edge results with the maximum accuracy of 99%.
In 2023, Priya Ujawe et al. [4] identified the diseases in rice plant using CNN. The publicly accessible dataset was utilized to identify rice crop diseases using the CNN inception V3 and squeeze net models, and these two models were compared. In 2023, Mu-Wei Li et al. [5] identified the water stress in rice plant using CNN. The authors suggested a rice water stress identification method that divided the irrigation status into three groups (100%, 90%, and 80% irrigation) using a CNN to

recognize water stress in thermal images of rice fields.
In 2022, Saleem Asif et al. [6] found the OsCML4 gene in rice related to salt stress using QTL Analysis. The genes found in [6] provide fresh genetic resources for enhancing rice's tolerance to salt in the future through molecular breeding techniques. In 2022, P. Sobiyaa et al. [7] classified the paddy disease using machine learning technique. The DNN approach achieved a high exactness of 91.9% for the blast impacted, 93.2% for the bacterial blight, 89% for the sheath rot, and 90% for the brown spot when compared to other classifiers**.**
In 2022, G. K. V. L. Udayananda et al. [8] diagnosed rice plant disease using machine learning techniques. The research offers a thorough understanding of the diseases that affect rice plants today and the deep learning techniques that are employed to identify the diseases. In 2022, M. K. Ramkumar et al. [9] identified genes for abiotic stress. In addition to offering a useful method for researching rice's abiotic stress tolerance, [9]'s work highlighted important candidate genes for abiotic stress tolerance that might be further confirmed by functional genomics.
In 2022, Gaurav Shrivastava et al. [10] identified the rice plant disease using machine learning. In terms of accuracy and time consumption, the practical research using the deployed system validates the superiority of ANN to be employed with the suggested decision support system over the SVM algorithm. In 2022, Harikumar Pallathadka et al. [11] detected the rice plant disease using machine learning. They introduced a machine learning architecture that uses CNN, SVM, and Naïve Bayes for leaf disease detection and classification.
In 2021, Ruoling Deng et al. [12] automatically diagnosed the rice diseases using deep learning. An automated diagnostic technique was created and integrated into a smartphone app. In 2021, Madhu Bala et al. [13] used deep learning and machine learning to identify the rice plant disease. After comparing several approaches for rice disease identification, it was determined that deep neural networks and decision tree classifiers could identify diseases in rice crops with the best accuracy >=97%.
In 2021, Junde Chen et al. [14] used Lightweight attention networks to identify rice plant illnesses, and the suggested process performs better than other cutting-edge techniques. On the public dataset, the obtained an average identification accuracy of 99.67%, and even in complex background conditions, the average accuracy for rice plant disease detection reaches 98.48%.
In 2020, Pooja S Warke et al. [15] classified and detected rice plant diseases using novel approach. The model achieved 93.33% training accuracy and 73.33% testing accuracy using support vector machines (SVM) to classify the disease. Additionally, k-fold cross validation for $k = 5$ and $k = 10$ was carried out. In 2019, Kandula Kushal Sai et al. [16] monitored and identified diseases affecting rice plants using a robotics technique based on the internet of things (IoT). The presented a concepts for an internet of things (IoT)-based smart agricultural pest robot that operated in rice fields, tracked readings, saved them in the cloud, and produced positive application outcomes.
In 2019, Lisu Chen et al. [17] detected Potassium nutrition stress in rice by using object-oriented segmentation and machine vision. According to the findings, at four distinct growth phases (productive tillering stage, invalid tillering stage, jointing stage, and booting stage), the overall identification accuracy of rice potassium nutrient levels was 90%, 94%, 94%, and 96%, respectively.
In 2019, Yuchao Feng et al. [18] conducted research on differential metabolites in rice origin distinction based on GC-MS. According to the findings, 173 peaks were found, and 54 of those peaks—which included sugar, polyols, amino acids, and aliphatic acids—were structurally characterized.
In 2019, Kawcher Ahmed et al. [19] identified rice leaf disease using machine learning techniques. The research revealed the presence of three of the most prevalent diseases affecting rice plants: brown spot, bacterial leaf blight, and leaf smut. In 2018, Weixuan Wang et al. [20] reviewed the rice secondary metabolites: structures, roles, biosynthesis, and metabolic regulation. The review concentrated on their understanding of rice secondary metabolite architectures, biological activities and roles, biosynthesis, and metabolic control.

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In 2023, Imran Zualkernan et al. [21] conducted a survey of 70 recent articles that used UAV agricultural photography to segment, identify, and categorize crops and trees using deep learning models and machine learning methods. Among state-of-the-art methods, deep learning models like ViT, YOLOv3, and U-Net did the best. In 2023, Ali M. Hayajneh et al. [22] frameworked for transfer learning empowered UAV assisted smart farming. Using time-series forecasting models, the framework was used as a case study to estimate soil moisture content for smart agricultural applications, directing the best use of water for crops.

In 2022, multiphotonic effects and machine learning technologies were coupled by Jose Alberto Arano-Martinez et al. [23] to increase the applications of optical biosensors. The authors of [23] provided an overview of optical biosensors' potential for viral detection. In 2021, Aditi Singh et al. [24] detected and classified the Potato Plant Leaves Disease using ML. The proposed framework achieved an accuracy of 95.99%.

In 2019, machine learning was used by Shrutika Ingale et al. [25] to identify plant leaf disease. In this study, the technological use of image processing technique for plant disease detection research was reviewed. In 2018, Plant disease was identified by Shima Ramesh et al. [26] by machine learning. In order to distinguish between healthy and unhealthy leaves from the generated data sets, the model used Random Forest.

In 2023, the artificial intelligence techniques known as Pattern Recognition (PR) and Deep Learning (DL) that have been developed over the past six years for data management have been compiled by Joel Serey et al. [27] according to the research, PR/DL techniques have been modified and applied more frequently to tackle different data management problems. In 2022, Santhana Krishnan Jayapal et al. [28] identified the tea plant disease using deep learning. The authors in [28] created an image retrieval model to determine if the input image of a tea leaf was healthy or diseased.

In 2021, Muhammad E. H. Chowdhury et al. [29] automatically detected tomato leaf disease using deep learning techniques. In conclusion that when deeper networks were trained on segmented images, all of the architectures fared better in the disease classification task. In 2021, Ebrahim Hirani et al. [30] detected plant disease using deep learning. In this study, these methods were contrasted with conventional CNN methods for the purpose of identifying plant diseases, and the transformer model's best validation accuracy of 97.98% was attained.

In 2021, Angel Fernandez Gambin et al. [31] focused on deep leaning strategies for water quality estimation and forecasting. They examined techniques and tools for evaluating water quality that support the long-term sustainable management of maritime habitats. In 2020, Murk Chohan et al. [32] used deep learning to identify plant disease. The proposed model achieved 98.3% testing accuracy.

In 2020, Reem Ibrahim Hasan et al. [33], detected Plant disease using deep learning. The most recent techniques for training, augmentation, feature fusion and extraction, identifying and counting crops, and detecting plant diseases were reviewed, looked into, and analyzed and also examined how these techniques can be used to feed deep classifiers and how they affect classifier accuracy.

In 2019, Muhammad Hammad Saleem et al. [34] detected and classified plant disease using deep learning. This analysis offered a thorough justification of the DL models that are employed to illustrate different plant diseases. In 2018, Omkar Kulkarni [35] detected crop disease using deep learning. In this work, a deep learning based model was presented, and it was trained using a public dataset that included pictures of crop leaves in both healthy and unhealthy conditions.

In 2022, El Mehdi Raouhi et al. [36] classified the diseases in olive plant using DCNN. In order to detect olive illnesses, their study included a dataset of 5571 manually gathered photos of olive leaves from various locations of Morocco. The photographs also included healthy ones. In 2016, Srdjan Sladojevic et al. [37] recognised plant diseases by leaf image classification using DNN. The created model was able to differentiate between plant leaves and their surroundings and identified 13 distinct plant disease kinds from healthy leaves.

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3. TYPES OF DISEASES IN RICE PLANTS

There are many numbers of diseases present in the rice plant. Even though, we have considered most important ninetypes of diseases present in the rice plant such as rice yellowmottle virus, rice blast, brown spot, sheath blight, sheath rot,leaf scald, false smut, kernel smut and grain rot.

Table 1: Types of rice diseases. Source [1]

Diseases /Images	**Symptoms**	**Damages**	**Control methods**
1.Rice Yellow Mottle Virus (RYMV) 	Rice plants that are stunted if they become infected early. Fewer tillers in use. Leaf mottling and yellowing.	Early-stage infected plants suffer more serious harm than later-stage infected plants.	Planting resistant cultivars is the most economical and efficient method of managing RYMV.
2.Rice Blast ***Magnaporthe grisea*** *(Pyricularia oryzae)* 	The fungus causes lesions or patches on grains, panicles, nodes, and leaves.The spots have a point at either end and are longer than usual.	Yields may be 50% lower in cases of serious illnesses. The damage to upland rice is greater than that to lowland rice.	Planting resistant cultivars is the most cost-effective method of managing this illness. Steer clear of too much nitrogen fertilizer.
3.Brown spot **(***Cochliobolus miyabeanus)* 	Brown patches on the leaf and grain are the symptoms. Seedlings cultivated from contaminated seeds may get seedling blight.	Grain weight and quality are reduced. A brown spot might harm as many as 50% of seedlings.	The best strategy to manage brown spot is to cultivate your plants in healthy soil with enough fertilizer.
4.Sheath Blight **(***Thanatephorus cucumeris)* 	On the leaf sheath, sheath blight creates patches. Stricter conditions are caused by high humidity and warmth.	Severe infections cause a large number of leaves to die, and yields may drop by 20% to 25%.	There is no kind that is very resistant to the illness. Don't use excessive amounts of nitrogen fertilizer.
5.Sheath rot	On the top most leaf sheaths	The amount of crop losses	Little is known about managing

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(*Acrocylindrium Oryzae)* 	enclosing panicles, spots form. Grains remain unfilled or are discolourd	brought on by sheath rot is unknown.	this illness.
6.Leaf scald (Metasphaeria albescen s) 	Lesions that begin at the tip of the leaf are the symptoms.	Grain quality and the filled grain ratio are decreased.	Steer clear of too much nitrogen fertilizer.
7.False smut (Clavice ps virens) 	A single panicle grain is transformed by the fungus into velvety balls that can enlarge to a diameter of one centimeter.	Usually, this condition does very little harm.	In most cases, no control measures are required.
8.Kernel smut (Tilletia barclayana) 	The grain surface has a black stain. The grain has a lot of black powder inside it.	Usually, this condition does very little harm.	Usually, no control measures are necessary.
9.Grain rot (Burkholderia glumae) 	Spikelets typically lose their green color and turn yellowish before becoming brown two days after heading.	Its lower grain quality and weight.	Although there are a number of fungicides that efficiently prevent grain rot, the tropics do not utilize them due to cost concerns.

4. METHODOLOGY

The following methods are used for detection ofdiseases in rice plant.

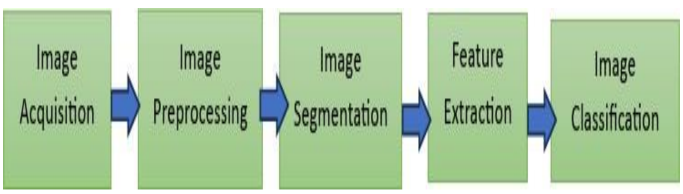

Figure 1: Block diagram for rice plant disease detection

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A. Image Acquisition

The process of retrieving an image from a source which could be a dataset or the manual capture of images is known as image acquisition [13]. Various sophisticated digital cameras are used to capture photos of diseased leaves during the image acquisition process [11].

B. Image Preprocessing

The goal of image preprocessing is to improve certain aspects of the image that are necessary for additional processing, such as resizing, cropping, and noise reduction [13]. Because thepictures in the image collection may have varied forms, it is necessary to resize the images equally and give identical height and width to each image in the dataset [11]. Authors in [12], considered the original image (rice leaf) size of 3264x2448 pixels. To lessen the model's computational strain, they scaled the image's long side proportionately and its short side to 256 pixels. Then, they applied the image to random affine transformation, which could randomly translate, rotate, scale, deform, and cut the image. At the same time,Gaussian blur and image flipping were applied randomly.Finally, the resized image was randomly cropped to a 224×224 pixels square area as the actual training image. These processes favored expanding the data set and reducing the over fitting of the model on the original dataset without modifying the characteristics of rice diseases [12].

C. Image Segmentation

In object identification tasks, segmentation is a crucial stage that converts images into a more relevant and easier-to-analyze format [13]. Instead of utilizing irrelevant segments of the input picture, just the infected section of the image is retrieved in image segmentation [11]. As a result, the enormous size of the inputimage is decreased, and the needless overload of training is greatly reduced [11]. A leaf disease diagnostic system was developed using a variety of segmentation techniques, including the Otsu segmentation method, K-means clustering, region segmentation, contours, etc. [13].

D. Feature Extraction

The authors of [38] utilized a discrete wavelet-basedfeature extraction approach to detect fungal diseases and reduced characteristics using principal component analysis (PCA). Authors in [8] used the deep-CNN (DCNN) forfeature extraction. In [8] main objective was to achieve good accuracy by extracting invariable features of rice infections by using deep-CNN model.

E. Image Classification

The four supervised classification machine learning methods (K-nearest neighbor, Naïve Bayes, decision tree (J48), and logistic regression) were employed by the authors in [19] to identify three illnesses (leaf smut, bacterial leaf blight, and brown spot) of rice leaves using a dataset. They [19] concluded that, the decision tree performed the better accuracy of 97.9167% on test data, among these four machine learning algorithms. Authors in [10], were implemented the plant leaf classification model using SVM and ANN classifiers. In their classification model [10], theyexperimentally proved that, ANN model is more accurate andefficient than SVM model. The deep-CNN model outperformed the other machine learning models, according to the authors in [8], who compared the models' accuracy, recall, precision, specificity, and F1 score. The models included KNN, SVM, random forest, Naïve Bayes, and deep-CNN.

5. INTELLIGENCE TECHNIQUES

A. Machine Learning

A number of classifiers are available in machine learning, such as convolution neural network (CNN), Naive Bayes, K-nearest neighbor (KNN), support vector machine (SVM), and backpropagation

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neural network (BPNN) [11]. Authors in [11] achieved the accuracy of 96.2% after preprocessing with histogram equalization of input images using SVM, which was more accuracy as compared to the CNN and Naïve Bayes machine learning algorithms. In [19], authors compared four machine learning algorithms—logistic regression, K-nearest neighbor, decision tree (J48), and Naïve Bayes—using a dataset of rice leaf diseases to identify three diseases: brown spot, bacterial leaf blight, and smut. They found that, out of these four algorithms, the decision tree had the best accuracy, scoring 97.9167% on test data.
The decision support model for the detection of rice plant diseases was created by the authors in [10] utilizing machine learning techniques including SVM and ANN. Experimentally they [10] had proved that, ANN performed better than SVM in terms of accuracy and time consumption.
Using machine learning techniques, the authors in [8] categorized paddy diseases such rice blast, bacterial leaf blight, sheath blight, and healthy leaves. The performance characteristics of various machine learning models, including KNN, SVM, Naïve Bayes classifier, random forest, and deep-CNN, were compared by them [8] with respect to specificity, accuracy, recall, precision, and F1 score. Experimentally they [8] had achieved the 93%, 93%, 96%, 89% and 95% of the accuracy, recall, precision, specificity and F1 score respectively, for deep-CNN, which was the better result than other models.

B. Deep Learning
Machine learning includes the deep learning technique. In deep learning, neural networks are used to model and solve complex problems [4]. Among the most well-known deep learning designs are convolutional neural networks (CNNs), recurrent neural networks (RNNs), and deep belief networks (DBNs). Authors in [4] were identified the diseases in rice plant using CNN inception V3 and squeeze net models and compared these models with different parameters like number of images, image size, epoch, accuracy and loss, finally concluded that inception V3 performed better than the squeeze net. Based on a sizable dataset comprising 33,026 photos of the six different forms of rice diseases—leaf blast, false smut, neck blast, sheath blight, bacterial stripe disease, and brown spot—authors in [12] created an autonomous deep learning detection system for rice disease. The ensemble model, which combined sub-models, served as the method's central component. Lastly, an additional set of photos was used to validate the ensemble model. According to the results, the top three sub-models in terms of a number of characteristics, including learning rate, precision, recall, and accuracy in identifying diseases were DenseNet-121, SE-ResNet-50, and ResNeSt-50.
After comparing several techniques for detecting rice plant diseases, the authors in [13] came to the conclusion that deep learning techniques hold greater promise than machine learning techniques.

6. HARDWARE AND SOFTWARE SPECIFICATIONS

A. Hardware specifications
The trials and findings are obtained using a Dell G15 5530 64-bit Operating System Windows 11 Home, x64 based processor with a 6GB NVIDIA GeForce RTX 3050 Graphical Processing Unit (GPU). The system was equipped with a 13th generation Intel(R) Core (TM) i7-13650HX CPU, clocking at 2.60GHz, with 16GB of RAM.

B. Software Specification
To implement the rice plant diseases detection model using machine learning and deep learning, we used the software platform of Python version 3.12.2 (64 bit)

7. PERFORMANCE ANALYSIS

A. Evaluation Metrics

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Authors in [14] considered the statistics of accurate detections (true positives), misdetections (false negatives), true negatives, and false positives, they performed an exhaustive analysis of the results output from different CNN models. Plant disease detection performance was evaluated using a range of metrics, including F1-Score, specificity, precision, sensitivity (recall), and accuracy, as stated in equations. (1–5) [14].

$$\text{accuracy} = (TP+TN) / (TP+TN+FP+FN) \quad (1)$$
$$\text{sensitivity} = TP / (TP+FN) \quad (2)$$
$$\text{specificity} = TN / (TN+FP) \quad (3)$$
$$\text{precision} = TP / (TP+FP) \quad (4)$$
$$\text{F1 Score} = 2TP / (2TP+FN+FP) \quad (5)$$

where true positive (TP) denotes the positive data label which is accurately identified; false positive (FP) is a negative data label which is mistakenly identified; true negative (TN) is a negative data label that is identified correctly; false negative (FN) is positive data label which is identified incorrectly.

CONCLUSION

In conclusion, the nine types of rice diseases such as rice yellow mottle virus, rice blast, brown spot, sheath blight, sheath rot, leaf scald, false smut, kernel smut and grain rot were considered for the investigation of rice plant. The survey included approximately thirty-six journal and conference articles, among which nineteen articles related to rice field, six articles related to machine learning models, nine articles related to deep learning models and two articles based on convolutional neural networks. This survey concluded that deep learning model performs better than the machine learning model. By harnessing the power of machine learning and deep learning, we contribute to the advancement of precision agriculture and sustainable food production practices.

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