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Analysis of Machine Learning Models Used to Diagnose Rice Plant Diseases-A Review

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Abstract: As the Indian population is increasing at a faster rate, agricultural productivity also needs to be rapidly increased. Rice is considered the essential food crop in India. However, the rice crop tends to be easily affected by disease-causing agents which results in decreased yield. Though various challenging issues degrade crop productivity like pests, climate changes, and diseases, crop diseases remain the main problem in rice cultivation. Most of the diseases are introduced by or associated with bacteria or fungi and can affect the crop in almost all stages from nursery to harvesting. Conventionally, human vision-based approaches have been employed to detect leaf diseases. They require expert knowledge, a laborious, and expensive process. In addition, the accuracy of the human vision-based process is mainly based on the vision of the farmer or experts. To resolve the limitations of classical approaches, it is needed to design automated Machine Learning (ML) based classifier models. Earlier identification of Rice Plant Diseases (RPD) enables us to take preventive actions and reduce the loss of productivity. This article suggests that the use of machine learning methods in this field has made a significant difference in the farming and productivity sectors, particularly given the more recent Deep Learning, which appeared to have enhanced accuracy levels. This paper emphasizes the study of various diseases on Rice plants along with various methodologies that are adopted for the detection, classification, and prediction of disease early.

Keywords: *Rice plant disease, Faster R-CNN, transfer learning, Resnet, convolution neural networks.*

1. Introduction

Rice is one of the primary crops in India the economy remains primarily reliant on agricultural products by approximately 70 percent. Yet, natural disasters, the environment, and unanticipated plant diseases make productivity in agriculture precarious. Farmers and manufacturers of products find it challenging to recognize and identify diseases of plants with their own eyes. Include the current statistics of the rice production year-wise and area-wise.

The present disease identification approach is a manual, so farmers need primarily to depend on instruction manuals for identifying diseases. Each plant disease occurs at various frequencies, Farmers must track the infection whenever the disease damages a plant. The process of disease evaluation requires time, and selecting appropriate pesticides requires precaution. Farmers could discover this attractive to utilize images of "seemingly infected" leaves which were recently handled using an automated technique. To help better agricultural practices and enhance crop management, the use of DL has also been studied in the field of plant diseases and agriculture. Difficulties in the agricultural industry's operations may influence the economies of countries that rely heavily on this industry. These decreases may be caused by a variety of sources, some of which may be abiotic. For researchers utilizing unsupervised models, certain limitations remain to present obstacles. In the beginning, we explore different techniques for image processing that evaluate input images using techniques for extracting features like GLCM and HAAR wavelet transforms in addition to techniques for segmentation including clustering, thresholding, and the watershed of features. Subsequently, this article gives a review of techniques for various machine learning algorithms, emphasizing the year of publication, the types of diseases, the precision of disease detection and classification, and finally the potential for future and present research work's barriers. The present research examines the use of machine learning and image processing for recognizing diseases in rice tissues from plants.

These field-captured images are preprocessed, the polluted leaf segments are obtained, the features are subsequently extracted from the segmented images, and finally, machine learning methods utilize these features to identify the disease. The efficiency of such a system depends on the accuracy with which it conducts image processing and machine learning actions. By examining the accuracy of the machine learning algorithms, the performance of a plant disease detection system can be measured. The collection of data on a deep learning network enables an extensive

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amount of self-adaptation one hand, throughout the data training process, there is an introduced chance of overfitting the noise and outliers. This issue extends the period between training and testing and reduces the accuracy of predictions made using actual test data. For instance, overfitting produces a high-order polynomial output in clustering or classification-related applications. This output determines the training dataset's determination limit, requiring more time and provides less accurate outcomes across nearly the whole test dataset. One way to deal with the overfitting problem is choosing wisely the amount many neurons in the hidden layer to match the problem type and size.

1.1. Rice Plant Diseases

The objective of including this part is in order to assist readers understand which types of image processing processes would be needed and what types of features would need to be taken into consideration while developing such a disease detection system.

1.2. Leaf blast

Use Leaf blast, also known as rice blast, is a destructive fungal disease that affects rice plants (Oryza sativa). It is caused by the fungus Magnaporthe oryzae. This disease is one of the most significant threats to global rice production, causing substantial yield losses in rice-growing regions around the world. Symptoms of leaf blast include lesions on leaves, stems, and panicles (flower-bearing structures) as shown in Figure 1.

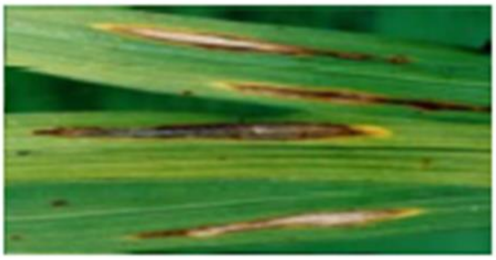

Fig.1. Leaf blast

These lesions can vary in appearance, ranging from small, circular spots with gray centers and dark borders on leaves to elongated lesions on stems. In severe cases, the lesions can merge and cause extensive tissue damage, leading to reduced photosynthesis, weakened plants, and ultimately reduced grain yield. This condition is characterized by dark, oblong spots with fine, reddish-brown edges and a grey or white center.

1.3. Brown spot

Brown spot, also known as Helminthosporium leaf spot, is a common fungal disease that affects a variety of plant species, particularly those in the grass family (Poaceae). This disease is caused by several species of fungi belonging to the Helminthosporium genus, now reclassified as Bipolaris, Curvularia, and Exserohilum genera.

Fig.2. Brown spot

Symptoms of brown spot disease typically appear as small, oval to elongated lesions on the leaves of affected plants. These lesions can range in color from light brown to tan and may have a darker brown border as shown in figure 2. Over time, the lesions may coalesce, leading to larger areas of infected tissue.

In severe cases, the lesions can cause significant damage to the foliage, impacting photosynthesis and overall plant health. Brown spot is favored by warm and humid conditions, which promote the growth and spread of fungal pathogens. The disease often occurs in areas with dense plantings, high humidity, and poor air circulation. It can be spread through rain splash, wind, and equipment that meets infected plant material.

1.4. Sheath blight

Sheath blight, also known as Rhizoctonia sheath blight, is a destructive fungal disease that affects a variety of grasses, with rice (Oryza sativa) being one of the most economically significant hosts. The disease is caused by the fungus Rhizoctonia solani. Symptoms of sheath blight typically appear on the leaf sheaths, stems, and sometimes the leaves of the affected plants. The disease usually starts as water-soaked lesions that quickly enlarge and turn light brown to dark brown in color as shown in figure 3. As the lesions expand, they can girdle the stem or leaf sheath, causing the affected tissue to die. In severe cases, the disease can lead to lodging (plants falling over), reduced grain fill, and ultimately yield loss.

Fig.3. Sheath blight

The fungus that causes sheath blight has a broad host range and can survive in the soil as mycelium or sclerotia (hard, survival structures). The disease is favored by warm and humid conditions, and it can spread through contact between infected and healthy plants.

1.5. Leaf scald:

Leaf scald, also known as bacterial leaf scorch, is a plant disease caused by the bacterium Xylella fastidiosa. This bacterium is responsible for a range of diseases in various plant species. Leaf scald primarily affects trees, causing symptoms similar to water stress and leaf damage.

Symptoms of leaf scald include browning and scorching of leaf margins, similar to symptoms seen in drought-stressed plants. The browning typically starts at the edges of the leaves and progresses inward, often following the veins. Over time, affected leaves may become necrotic, giving the appearance of burned or scorched foliage as shown in Figure 4. In some cases, leaves may drop prematurely.

Fig.4. Leaf scald

Xylella fastidiosa is a xylem-limited bacterium, meaning it resides in the water-conducting vessels of the plant. It disrupts water movement within the plant, leading to symptoms that mimic water stress even when adequate water is available in the soil. The disease is spread primarily by xylem-feeding insects such as leafhoppers and spittlebugs.

Bacterial leaf blight typically manifests as dark or water-soaked lesions on plant leaves. These lesions can vary in size, shape, and color depending on the specific bacterial pathogen and the host plant as shown in Figure 5. The disease often spreads through water droplets, rain, or irrigation, which help disseminate the bacteria from infected to healthy plants. It can be particularly problematic in crops and plants that are susceptible to bacterial infections.

Fig.5. Leaf blight (Bacterial)

It was utilized for connecting and combining contextual and visual data. The surrounding environment surrounding the plant, comprising components like temperature and humidity, which may lead to or assist to various diseases, was the focus of the contextual information. The recognition phase, where 97.50% accuracy was attained, was enhanced by the categorization of these characteristics. Due to the difficulty of gathering photographic samples that span a wide variety of crops in different environmental circumstances, dataset restrictions are an issue. The Deepest model was used to identify pests in crops; it had an inference time of 120ms and could recognizes minute features like pests. The model used a cascade of detecting processes. Prior knowledge for the classifier was first learned using a two-level Decision Net by leveraging contextual data that was collected from cropped images.

2. Related Work

A research study on the detection and classification of plant diseases was carried out by Jayme Garcia et al. In addition, the severity of the disorders was discussed. In their study, various images are briefly indicated. Approaches for processing and machine learning, include region growth, neural networks, dual segmented regression analysis, measured color analysis, and fuzzy logic. Rashmi Pandey et al.'s [21] assessment of the image processing and ML methods used in fruit grading systems can be found at. Grading the fruits entails sorting the fruits based on their size, texture, stem, shape, color, and calyx. The most important element of an image is its color. The report provided a quick overview of various color feature extraction approaches.

The article also covered the comparison of several machine learning techniques, including rule-based systems and support vector machines. A technique to identify rice and rice blast diseases was presented by Yang et al. in 2019. The microscope image is used as an input and identifies the disorders in this paper. For the segmentation of backer spores in photos, the watershed method was applied. Extracted texture and form features are supplied as classification input to the decision tree model.

The achieved detection accuracy for classification accuracy as measured by the confusion matrix approach was 94%. Using image-processing methods, Larijani MR, et al. (2019) [22] describe a method for early diagnosis of rice blast illness. Improved k-NN and K-means were used in this study to categories the disorders using lab color space. Images that were partitioned were segmented using the Otsu method. Extrapolated aspects of shape and color were used for classification.A system to recognise and categorise the diseases Rice blast, bacterial blight, and sheath blight was proposed by Zhou, et al. (2019)[12].

Otsu's threshold method was utilised to lessen the background portion's interference with locating the necessary region. The optimal values of k are calculated using the FCM-KM technique. FCMKM and Faster R-CNN are combined to identify rice illnesses. For rice blast, bacterial blight, and blight, respectively, disease detection accuracy was 96.71%, 97.53%, and 98.26%. A technique to recognize the illnesses Leaf Blast, Brown Spot, and Leaf Blight in paddy leaf was proposed by Shreekanth, et al. (2019) [1]. Otsu's approach was used to divide the image. For classification, wavelets and texture features are used. Using a feed-forward neural network (FFNN) for classification gives information on several image processing and ML methods utilized for plant disease diagnosis utilizing images of leaves. A device-independent color space transformation is first applied to the color transformation structure after it has been generated. There are several pre-processing techniques given, including clipping, image smoothing, image enhancing, and histogram equalization. Additionally, a brief description of segmentation methods such as K-means clustering, thresholding, boundary detection, and spot detection is provided. Important characteristics including color, texture, morphology, and edges are also covered. The working principle of classification based on ANN is discussed.

3. Data Collection and Pre-Processing

The image databases especially for rice disease images are presented at International Rice Research Institute (IRRI). Hence, we must make image databases by ourselves that need the acquisition of images from the live farm. In the procedure, images can be taken from the farm through a digital camera to attain them straightaway in a digital format with arithmetical value in such a way digital image processing operation is performed.

3.1. Data pre-processing

In order to get effective outcomes in further steps, image pre processing is needed since dewdrops, dust, and insect excrement might be existing on the plants; such things are considered as image noise. Moreover, the captured image might have distortion of shadow effect and water drops that might pose challenges in the feature extraction and segmentation process. Effects of this distortion could be removed or weakened by discant noise removal filters. Occasionally, a background removal process might also be required in case of ROI that should be extracted. There might be lower contrast in captured images; for those images, a contrast enhancement algorithm is employed. In the case of the image captured by higher-resolution cameras, the picture size could be larger, for this image size reduction is needed. In case of noises like salt and pepper, Median Filters (MF) are employed. Weiner filters are employed for removing blurring effects. As well, image reduction assists in decreasing the computational memory.

The researchers have enhanced images using an array of techniques, such as mean filtering, histogram equalization, and the Laplacian filter. Because greenness has a greater impact when a disease appears on a leaf, they tried to enhance the affected portion of the leaf by eliminating the green element of the image.

3.2. Realistic Datasets

Collecting datasets is an obstacle to academics since any Deep Learning model can become more precise using enormous amounts of data. The largest open-access database of crop images can be seen by the Plant Village dataset that was used in.

It includes images of both wholesome and disease-free crops with various kinds of fungi, bacteria, mold, viruses, and mites. The samples in this repository have all had their leaves plucked from their plants and are shown against a grey background with professional labels. The findings of diagnosis models, when they are trained using leaf image samples that are plucked from the plant and those obtained in fields, differ, according to recent research. Recent research efforts indicate that training models for diagnosis employing leaf images that are collected from the plant and those that are taken in fields generate distinct results. The variance in results is viewed as an issue in the effectiveness of detection models. New sources have become available that provide fewer copies of leaf/fruit images for related/different species as a result. Large datasets that contain a broad array of parameters that must be tweaked to control training convergence are necessary to train a DL classifier. It is thought to be a very difficult effort to manage all the suggested model's parameters (bias, weights, learning rate, mini-batch size, and epochs) according to random Gaussian distributions. Starting from scratch requires a lot of information and time. Because there are now vast, many-labeled, and well-annotated dataset repositories, researchers no longer need to gather enormous datasets in various real-world settings that would require the guidance of agricultural specialists to be evaluated.

4. Methodology

A family of deep learning models known as convolutional neural networks (CNNs) are created particularly for processing and analyzing structured grid-like input, such as pictures or time series data. CNNs are frequently employed for computer vision applications such as picture segmentation, object identification, and classification.

The key building blocks of CNNs are convolutional layers, which perform convolution operations on the input data. The convolution operation involves sliding a small filter (also known as a kernel) across the input data and computing the element-wise multiplication and summation of the filter and the corresponding input values. This process helps the network extract spatial features from the input.

The architecture of a CNN typically consists of multiple convolutional layers as shown in figure 2, interleaved with pooling layers, followed by one or more fully connected layers. This architecture allows the network to learn hierarchical representations of the input data, with lower layers capturing low-level features (e.g., edges and textures) and higher layers capturing more abstract features (e.g., object shapes and configurations).

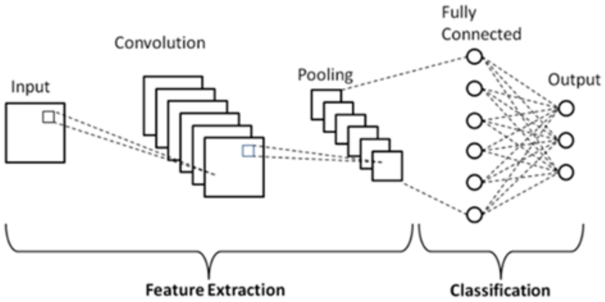

Fig.6. Architecture of convolution neural networks

During the training process, CNNs learn to optimize their internal parameters (weights and biases) by minimizing a predefined loss function using methods like gradient descent. The backpropagation algorithm is commonly employed to efficiently compute the gradients and update the parameters.

CNNs have achieved remarkable success in various computer vision tasks and have been instrumental in advancing state-of-the-art performance on image-related problems. Their ability to automatically learn hierarchical representations and capture spatial dependencies makes them well-suited for processing grid-like data.A CNN model can pick up weights from another model that has already been pre-trained on a sizable labeled dataset using transfer learning. Using the Image Net dataset with an adapted learning rate that was slower than the default rate, all of the layers that make up a CNN model were modified. The last entirely connected layer was randomly initialized and taught to be sufficient for the new classes, but the researcher said it was very difficult to determine the suitable learning rate for the other, deeper layers. A different study compared the usage.

Recent years have seen the development of numerous CNN designs; according to, the DenseNet structure may reach nearly the same degree of accuracy as ResNet with fewer parameters. By using batch normalization, residual learning, and non-CONV layers, these models enhance their prediction phase. Convolution filter sizes were decreased in both architectures, which resulted in smaller filters than in the VGG and previous architectures. This decreased computing time.RCNNs are two-stage creates enabling object detection. The ROI is filtered in the Faster-R-CNN version using the fully convolutional region proposal network, and the filtered features are then shared with a detection network known as the ROI pooling network, ensuring a quick and accurate extraction procedure. However, there is a quantization issue with this approach that affects ROI prediction.

The modified Faster-R-CNN model called Mask R-CNN, which was employed in was therefore given a ResNet-feature pyramid network (FPN) backbone. Small item detection and improved semantic segmentation were made possible by the FPN. Additionally, pixel-to-pixel alignment was used in place of ROI pooling, and all the computational parameters of the features were taken into consideration.YOLOs, on the various hand, are single-stage object detection buildings. Yolo-v3 is a real-time architecture that has been developed for predicting numerous classes from an input image without requiring any sort of pre-determination procedure. It was built on a system like FPN, which made its feature extraction robust. The SoftMax function that activates was replaced with a cross-entropy function, enabling multiple class recognition. It was additionally quicker than Single Shot Detector (SSD) because DarkNet-53 served as its backbone. Retina Net's performance was found to be somewhat more useful than Yolo-v3's.

It used an FPN as the classifier's backbone, which enhanced cross-entropy performance by introducing a variable factor that decreased the number of missed classified instances during training.

Table 1. An overview of the various algorithms used in the diagnosis of rice plant diseases

Author&year	**Disease type**	**Algorithm**	**Accuracy**	**Limitations**
Shreekanth K.et.al (2019) [15]	Leaf Blast, Brown Spot	Feedforward Neural Network	83.3% for three and 99%for two Types of diseases.	Accuracy is low. Only three diseases are covered.
Nidhis A. D.(2019) [14]	Bacterial Blight Brown Spot	K-NN, Naive Bayes and Logistic	97%	Low accuracy The quality of datasets can be improved.

		Regression		
Prabira Kumar Sethyet al.(2019)	Brown spot Rice blast	Naïve Bayes and SVM	79.5% for Bayes and 68.1% for SVM	Few diseases are covered
Kawcher Ahmed et al.(2019) [16]	Bacterial Blight, Leaf Smut, and Brown spot	Texture Analysis and PNN	83%	Low accuracy
Sethy, P. K., Barpanda, N. (2020) [17]	Bacterial blight Brown spots Rice blast	SVM	97%	MobileNetV2 and shuffle Net were evaluated
Pothen ,M. E.(2020) [18]	Bacterial Brown spot Leaf smut	SVM	LBP: 90% HOG: 94.6%	LBP: Texture HOG: Shape
Ramesh S. et al.(2021) [13]	Rice Blast	ANN	89%	It will not classify types of diseases.
Prajapati H. B. et al.(2022) [23]	Bacterial Blight, Leaf Smut Brown Spot	SVM	92.43% , and 72.43% .	Low accuracy
Larijani Mohammad Reza et al. (2019) [19]	Rice Blast	KNN	93.9%	It will diagnose Rice Blast Disease only
Ahmed, K., Shahidi, T.(2019) [1]	brown spot bacterial blight sheath rice blast	MDC and KNN	k-NN => 87.02 % MDC => 89.23 %	Color and shape
Vydeki, D. (2018) [20]	Bacterial Blight	ANN	For training: 99% & 100% For testing: 89%	Mean, SD, GLCM (Energy, Contrast, Correlation, Homogeneity)
Asfarian Auzi et al. (2019) [24]	Leaf Blast Bacterial Blight Brown Spot	Texture Analysis and CNN	83%	Low accuracy. Works on the lower dataset
Md Ershadul Haque et.al (2022) [25]	Blight BrownSpot RiceBlast Bacterial Leaf	Back Propagation	98%	Few diseases are covered

5. Observations

In this study, several pertinent publications concerning the diagnosis and classification of plant diseases are chosen. These studies have been presented at conferences and published in several reputable journals. This article's main goal is to identify uncharted territory that might be further investigated. All research articles that have been assessed have their conclusions and future scope sections carefully examined to find any research gaps. During our effort, we have discovered the following research gaps:

1. Only a small number of the approaches in the review have accuracy ratings of 99% or above.

2. Most of the picture samples in the benchmarked plant disease dataset just have the illness name labeled; they do not include labels indicating the disease's intensity or severity. An infection severity estimation approach may be created to create a new dataset labeled with disease intensity from an existing plant disease dataset in order to solve this problem.

Convolution neural networks-based models are giving good accuracy and other advantages are there. So if we extend this model with transfer learning may give good results.

6. Conclusion

Rice plant diseases and agriculture might suffer a significant amount of loss. An automated system capable of delivering early disease notifications can be constructed using computer and communication technology. We have investigated the fact that there are many solutions for various machine learning and image processing procedures. This work analyzed and compiled the machine learning and image processing techniques that have been used to identify illnesses. The many machine-learning models used to identify illnesses in rice plants are summarized in this article.

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