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Rice Leaf Disease Detection Using Deep Learning Algorithm

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Abstract

Rice cultivation faces significant challenges due to diseases such as bacterial blight, Blast, brown spot, and tungro, which diminish the production and quality of crops. Additionally, traditional methods of detecting these diseases are difficult and prone to mistakes. This situation worsens production losses and risks food security. This research seeks to overcome this issue by examining the effectiveness of deep learning techniques, particularly Convolutional Neural Networks (CNNs), in automating the detection of rice leaf disease. We collected a diverse data set consisting of 6229 pre-processed photos of common rice leaf diseases and healthy images. This dataset was used to train the CNN model, and performance was assessed using evaluation measures including confusion matrices and accuracy assessment. The results showed significant performance improvements, with the CNN model obtaining a final validation accuracy of 98.98%. In detecting rice leaf diseases, our method exceeded other deep learning systems. In places where rice production is the primary source of food security, this work highlights the potential of CNN-based models in automated rice disease detection, providing an effective way to improve crop productivity.

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1 Introduction

Rice (Oryza sativa) is a major food crop that is essential for maintaining food security and human nourishment across the world. For more than half of the world's population, mainly in Asia, it is their main source of sustenance. More than 100 nations cultivate rice, a staple crop for more than half the world's population, with Asia accounting for 90% of worldwide output and it is grown on around 160 million hectares of agricultural land globally [1]. The world produces 755 million tons of rice, produced over an area of 165 million hectares, with annual fluctuations in cultivation [2]. Presently, more than 100 nations cultivate rice, yielding about 715 million tons of paddy rice and 480 million tons of milled rice; 90% of the rice produced worldwide is accounted for by 12/15 nations, the demand for rice [3]. The International Rice Research Institute (IRRI, 1998) projects that the dramatic decline in per capita water supply would cause hardship over the next 20 years for India, Pakistan, the Philippines, and Vietnam. According to estimates, Asia's urban population will increase from over 35% of the continent's total population in 1990 to over 50% by 2025 [4].

Ninety percent of the world's rice is produced in Asian nations, which also include Indonesia, Bangladesh, Vietnam, Myanmar, Thailand, the Philippines, Japan, Pakistan, Cambodia, the Republic of Korea, Nepal, and Sri Lanka. Egypt, Brazil, the United States, Madagascar, and Nigeria are the other main non-Asian rice producers, contributing 5% of the world's rice production [3]. China and India are the two biggest producers of rice in the world. Because rice is grown in irrigated regions, China produces more rice than any other country. Rice is highly suited to a range of Agro-climatic circumstances, and it is now farmed at high and low altitudes in both wet and dry land environments. Figure 1 and Figure show the demand for rice worldwide [5].

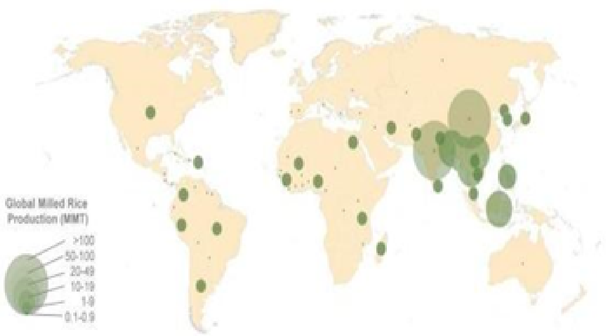

Figure 1. Worldwide rice production

Asia's population is predicted to expand by 53% by 2025, and during the following 30 years, demand for rice is estimated to rise by 70%. Because of this, irrigated rice will need to meet a significant amount of this increased demand in the future. On the other hand, irrigation is not prioritized above urban and industrial needs. Due to these circumstances, rice paddy cultivars are being forced to be produced on marginal land that receives low-quality water irrigation [6]. One of the major constraints to rice production worldwide is rice diseases that reduce rice production to a large extent. Pyricularia oryzae, which causes rice blast, poses a danger to the world's ability to produce enough food. The disease may cause crop failure because it damages tissues that are above ground [7]. Every year, brown spot (Horminthosporium oryzae) reduces worldwide yield by 5%; in some areas, this drop might reach 45%. The disease had already caused severe famine and millions of deaths after its rise during the Bengal Famine of 1943. In modern contexts, brown spot is an enduring issue despite efforts to employ chemical treatments, biological controls, and resistant cultivars [8]. However, several variables, including biotic pressures such as leaf diseases, threaten the regular and dependable production of rice. These diseases, which are brought on by pathogenic microorganisms, dramatically lower rice output and quality, causing financial losses and a shortage of food [9].

Due to human error and time consumption, traditional techniques' efficacy in detecting rice leaf diseases is limited. Rapid and accurate detection of leaf diseases is critical for preserving crop yield and quality, particularly with the growing global demand for rice production. The methods now in use for detecting rice leaf disease frequently depend on manual inspection, which is time-consuming and prone to subjective interpretation. Significant yield losses result from the delayed detection and treatment of rice leaf diseases due to a lack of resources and expert knowledge in distant places. Early detection and management of rice leaf diseases continue to be a significant problem, despite developments in agricultural technology. Therefore, the objective of the research is to investigate how well deep learning algorithms work for the automated and accurate detection of different rice leaf diseases. The research aims to improve the accuracy and efficiency of diagnosing and controlling rice leaf diseases by creating a strong system that can classify and detect diseases early. This would ultimately lead to increased crop yield and food security.

2 Literature Review

A study conducted by Poorni et al. [10] focuses on using Convolutional Neural Networks (CNN) and the Inception v3 model to automatically detect and combat rice crop diseases in India. The method achieves an excellent 94.48% accuracy by training on a wide set of photos related to rice leaf disease. Another study implemented several variables influencing grain quantity and quality that pose a danger to rice, an essential worldwide staple [11]. Conventional methods are less efficient and take more time. With an astounding average accuracy of 99.64%, InceptionV3 outperforms AlexNet, which performs comparably worse at 97.35%. Additionally, Krishnamoorthy et al, [12] showed that in more than half of the world's population, rice (Oryza sativa) is a staple meal and a crucial cereal crop. However, a variety of variables, including weather and infections, negatively impact its output and quality. Manual observation is the foundation of traditional disease management, which results in inefficiencies. Convolutional neural networks (CNNs), in particular, have shown great potential in agricultural technological advancements. Our study optimizes farming methods by automatically recognizing rice leaf illnesses with a high accuracy of 95.67% using the InceptionResNetV2 CNN model with transfer learning. Similarly, Bozcu [13] examines the use of deep learning and machine learning techniques to detect various diseases, assessing precision, recall, and accuracy. The results show that deep learning models outperform machine learning techniques; a 5-layer convolution model had the greatest accuracy of 78.2%.

In response, a different study suggested a method for quickly classifying paddy plants as healthy or sick, along with accurate localization of the afflicted regions [14]. With a dataset of 3500 photos from open platforms, the convolutional neural network (CNN) classification module produces results that are remarkably accurate—almost 70%. This work paves the way for future research initiatives in this important agricultural subject while also assisting with present issues. Another study presented a model for classifying and detecting several rice leaf diseases, such as hispa, brown spot, and leaf blast, using image processing techniques [15]. The CNN machine learning technique is used to implement the model, which achieves an astonishing 90% accuracy in detecting leaves damaged by disease from healthy ones. To overcome farmers' deficiencies in equipment and skill Kiratiratanapruk et al. [16] focused on the need for a quick, accurate, and reasonably priced technique for detecting rice diseases. The suggested method uses a model to predict leaf width for uniform subdivision of the input pictures and combines CNN object detection [17] with an image tiling methodology. With the suggested picture-tiling approach, the mean average accuracy increases from 87.56% to 91.14%, indicating improved efficacy in rice disease detection. Challenges like environmental conditions and differences in rice leaf item sizes are encountered by the research, which applies computer vision algorithms to real-world photographs from rice fields. According to a study by Islam et al. [18], common diseases including Brown Spot, Blast, and Bacterial Leaf Blight cause growers to suffer significant losses. The research assesses VGG-19, ResNet-101, Xception, and Inception-ResNet-V2 using an advanced automated method utilizing deep learning CNN models. Inception-ResNet-V2 achieves an outstanding accuracy of 92.68%. This surpasses conventional manual detection methods, indicating the possibility of revolutionary breakthroughs in the control of crop diseases.

Moreover, Latif et al. [19] presented a new approach to Deep Convolutional Neural that integrates drone technology, the Internet of Things (IoT), and machine learning. In detecting and detecting six different rice leaf diseases, the suggested Deep Convolutional Neural Network (DCNN) transfer learning approach—specifically, a modified VGG19-based method—achieves an astounding average accuracy of 96.08%. This creative integration offers a revolutionary and economical method to improve rice disease detection. Also, research recognized the detrimental effects of deadly diseases on agricultural productivity [20–22]. Khan et al. [20] tackled the rising need for rice in the face of an expanding world population. The imprecision and inefficiency of current approaches for detecting rice disease have been criticized. In this work, a novel hybrid model consisting of Self-Attention (SA), Long Short-Term Memory (LSTM), and Convolutional Neural Network (CNN) modules is presented. With strong confidence intervals, ROC-AUC rates, precision, recall, and F1-score, the model exhibits solid performance, achieving 100% accuracy in training, 97.51% in validation, and 100% in testing. The rice leaf disease detection confidence range for the model is 97.5%–100%.

In the area of crop production, Cho et al. emphasized the effects of plant diseases on crops while addressing the critical significance that agricultural production plays in the Indian economy [23]. It investigates the use of several algorithms for plant disease detection and suggests a CNN-based technique. With a test accuracy of 88.80%, the suggested procedure helps detect plant diseases. This research addresses frequent bacterial leaf blight in rice, a dangerous disease that can result in crop loss and a large drop in output. In the use of CNN, research shows the importance of rice as a staple grain around the world while drawing attention to the diseases that might affect paddy fields [24]. The suggested technique utilizes Convolutional Neural Networks (CNN) with pre-trained models such as ResNet-50, ResNet-101, VGG-16, VGG-19, EfficientNet, Inception-V2, and GoogleNet to detect paddy leaf diseases. The suggested detection technique classifies five classes of paddy leaf conditions with the maximum average accuracy of 96.27% for ResNet-50 and an F1 Score of 98.19%, making it more economical and time-efficient than standard laboratory procedures. A reliable technique for detecting rice plant diseases using convolutional neural networks (CNN) is presented [25]. The results demonstrate an astounding 99.7% accuracy, highlighting the rapidity and efficacy of the suggested strategy in precisely detecting and categorizing rice diseases.

In addition, a hybrid deep CNN transfer learning technique is suggested. Shafik et al. offered a novel method for detecting plant pests and diseases [26]. The model's remarkable 99.2% accuracy was demonstrated through experiments done on a dataset consisting of 4447 cases of apple pests and diseases across 15 classifications.

3 Methodology Section

3.1 Data Collection

A total of 6229 images of five common classes of rice leaf diseases, including Bacterial Blight, Blast, Brown Spot, and Tungro were collected from the source [27], and Healthy data was collected from the online website Kaggle. Since multiple sources are used to collect the data, there are differences in image sizes for different classes. For the Bacterial Blight, Blast, and Brown Spot the image sizes are the same that is 300*300 and the Healthy image size bit large that is 1881*1881 for the Tungro images is unpredictable for each image, but the image size range is between 200*200 to 300*300 pixels. For some images, the background is white and for some images, the background is the original crop field because real-time detection requires a trained model in the original background. In this case, the angle of the camera for taking pictures is also important because it is important to collect pictures of diseased leaves from different angles for the system to work properly during real-time detection. The Images collected for this project are stored in IMG file format. Table 1 shows the number of images in each class.

Data Type	No. Training Data	No. Test Data
Bacterial Blight	1109	475
Blast	1008	432
Brown Spot	1120	480
Tungro	916	392
Healthy	208	89

Table 1. Number of images in the dataset

3.2 Data Preprocessing

To ensure effective computational analysis, data preprocessing is essential for optimizing pictures for deep learning models. Before being input into the model, the initial images—which are frequently jumbled and come from many sources—need to be cleaned up and standardized. Normalization is one of the crucial preprocessing stages; it's especially crucial for jobs like image classification. Important parameters to restrict the number of photographs processed in each training iteration and standardize image dimensions to (224, 224) are batch_size and img_size. By ensuring numerical stability during training, rescaling pixel values to a range between 0 and 1 improves model generalization by fortifying it against changes in image attributes. For reliable model training and assessment, data splitting separates the dataset into training (80%) and validation (20%) sets. By exposing the model to a range of cases, data augmentation enhances the diversity of the training dataset and reduces the risk of overfitting. Preprocessing, in general, improves classification performance, guaranteeing the model's effectiveness in real-world use.

3.3 Algorithm

The model used in this project for rice leaf disease detection is the Convolutional Neural Network (CNN). Convolutional neural networks, often known as CNNs, are a unique kind of multilayer neural network or deep learning architecture that draws inspiration from living systems' visual systems. CNN is very appropriate for several domains in natural language processing and computer vision. An in-depth analysis of each of CNN's fundamental parts is the primary goal of this chapter. It also provides an overview of CNN's history, current developments, and some of its most important application areas [28]. Convolutional Neural Networks (CNN's) are successful because of their carefully thought-out architecture, which takes into account both local and global data features. CNNs include characteristics like hierarchical representation and local connectivity, which were initially created for effective image processing. Their broad range of uses has led to their employment in neurology and psychiatry to research brain problems [29].

Convolutional neural networks, or CNNs, are extensively employed in many different fields, such as image detection, object detection, and medical image analysis. Convolutional Neural Networks (CNNs) are a good choice for training on big datasets with millions or billions of parameters because of their remarkable efficacy in automatically detecting characteristics from pictures. The literature on CNN applications is reviewed in this work, including fields like document layout, medical, and agricultural. Numerous CNN models for image detection and detection are evaluated as part of the diseases, which offers a dataset-based comparative analysis. The purpose of the paper is to be a useful manual for newcomers to this field [30].

The activation function is a key component of Convolutional Neural Networks (CNNs), providing non-linearity to the model and allowing it to discover intricate links within the data. Rectified Linear Unit (ReLU) and SoftMax are the two main activation functions employed in the model. ReLU Activation Function: In the intermediate dense layer, the Rectified Linear Unit (ReLU) is utilized, and its formula is as the equation:

$$F(x) = \max(0, x). \tag{1}$$

In this case, x is the activation function's input, while 0 and x max are the function's outputs. ReLU creates non-linearity by setting negative values to zero and letting positive values go through unaffected.

SoftMax Function: The last dense layer for multi-class classification uses the Softmax activation function. The SoftMax function for a class may be found using the formula.

$$\sigma(z_j) = \frac{e^{x_j}}{\sum_{j=1}^{j} e^{z_j}}. \tag{2}$$

Figure 2 shows the process of the CNN algorithm [31].

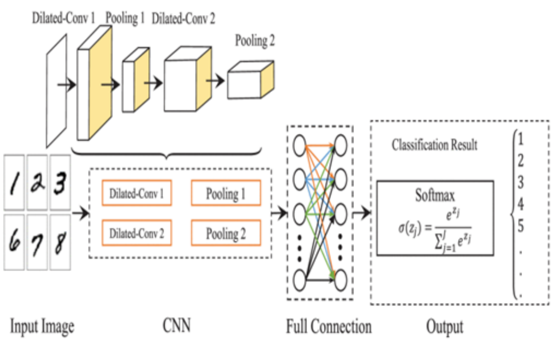

Figure 2. The working process of CNN

3.4 Evaluation Metrics

Addressing the project "Rice leaf disease detection using deep learning," choosing to use the confusion matrix and accuracy assessment metrics serves several important functions, especially in image processing and classification tasks.

Accuracy: Accuracy offers a clear assessment of general correctness and a brief rundown of the model's functionality. This statistic provides a clear baseline for evaluating the model's effectiveness in image processing applications such as rice leaf disease detection, where the ultimate aim is to obtain high accuracy in detecting sick and healthy leaves [32]. In a binary classification scenario (two classes, typically denoted as positive and negative), the accuracy has four entries: True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN). The equation is:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}. \tag{3}$$

4 Results and Discussion

To fully evaluate the model's performance, evaluation metrics including accuracy, loss, and confusion matrices were used. The model's resilience and capacity for generalization were further improved by the incorporation of strategies like early halting and class weights, which addressed prevalent issues like overfitting and class imbalances.

The Convolutional Neural Network (CNN) was trained on a diverse dataset comprising 6229 images, categorized into five distinct classes, with 30% of the dataset reserved for testing purposes. There were thirty epochs in the training process, with 137 steps in each. The model was continuously improved during this training process, which helped it to comprehend more complex patterns in the dataset. A training accuracy of 27.36% and a matching validation accuracy of 34.48% were found in the first period. The model demonstrated a consistent improvement in its performance measures throughout the epochs, demonstrating its ability to distinguish between various rice leaf diseases. A final training accuracy of 95.92% and an astounding validation accuracy of 98.98% in the last epoch were the outcomes of this learning procedure. Figure 3 shows the changing of validation and training accuracy as well as it shows the validation and training loss.

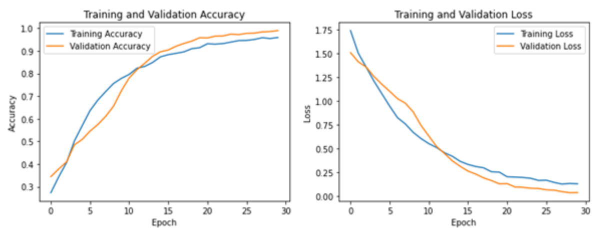

Figure 3. The training and validation accuracy and loss of CNN

A look at the validation loss throughout the training phase yields an understanding of the model's functionality. Validation loss serves as an important statistic for analyzing the model's generalization capabilities. Throughout the epochs, CNN consistently reduced the validation loss, with the last epoch seeing the lowest value of 0. 0403. The model's ability to reduce the difference between the predicted and actual classes on the validation set is demonstrated by the reduction of validation loss. This finding implies that the model can produce correct predictions on fresh, untested data in addition to being accurate on the training set. During the training phase, regularization methods and data augmentation were used sparingly to overcome overfitting problems. Even with the significant difference in performance between training and validation accuracies, the model was able to successfully generalize, providing accurate predictions on data that had never been seen before. Finally, with a final validation accuracy of 98.98%, the CNN model created for rice leaf disease detection shows promise and is a strong tool. Because of its remarkable learning powers and ability to generalize new data, it is a useful tool for automated rice disease detection.

There are notable differences in performance when the results of several deep learning algorithms for rice leaf disease detection are compared. With a training accuracy of 95.92% and a validation accuracy of 98.98%, the CNN model shows the highest accuracy, demonstrating its efficacy in extracting intricate patterns and features from the input data. While the RNN model shows a validation accuracy of 83.21% and a training accuracy of 82.40%, the VGG-16 model achieves a training accuracy of 84.62% and a validation accuracy of 85.89%. In comparison, both models show lesser accuracies.

Algorithms	Training Accuracy	Validation Accuracy
CNN	95.92%	98.98%
VGG-16	84.62%	85.89%
RNN	82.40%	83.21%

Table 2. Number of images in the dataset

These differences imply that CNN performs better in this area than VGG-16 and RNN, demonstrating its superiority in correctly diagnosing rice leaf illnesses.

5 Conclusion

"Rice Leaf Disease Detection Using Deep Learning" is an important resource for understanding and empowering agricultural industry stakeholders. The research process, which includes an introduction, a literature review, methodology, results, and discussion, represents a significant advancement in agricultural technology, especially concerning the detection of rice leaf disease. The Introduction focused on the importance of technical solutions for agricultural operations, particularly for disease detection, and began with a brief overview of the situation. The foundation was laid by an extensive literature review that detailed the situation of rice leaf diseases today and discussed how deep learning specifically, Convolutional Neural Networks (CNNs) can help with these problems.

To provide accurate model training and validation, the Methodology section describes the methodical approach to dataset collection, preprocessing, building models, and evaluation. Using CNN architecture, in particular, MobileNetV2 showed how to apply deep learning techniques to improve disease classification by using feature extraction. CNN was found to be more effective in detecting rice leaf disease when compared to other deep-learning methods. The prospective use of the CNN model as an effective automated method of rice disease identification, leading to increased production and food security, is highlighted by its capacity to generalize well to new and unknown data.

The project's outputs were thoroughly analyzed in the results and discussion section. Significant achievements were the construction of an intuitive real-time disease detection with a final training accuracy of 95.92% and an astounding validation accuracy of 98.98%, the effective extraction of features from images of rice leaves, and the remarkable performance of the model's training and validation. In the end, this research is about crop disease management using deep learning that promises to transform crop disease management and increase global food security, sustainability, and agricultural production. It is an outstanding instance of how collaborative research advances agricultural technologies.

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