Precision Agriculture: Enhancing Rice Leaf Disease Classification and Prediction with a Custom Convolutional Neural Networks

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Abstract: Accurate detection of rice leaf diseases is critical for maintaining crop health and promoting sustainable agricultural practices. Disease outbreaks in rice crops can lead to significant losses in yield, threatening food security and economic stability. Therefore, developing reliable and efficient methods for early and accurate disease identification is essential. This study introduces an enhanced methodology that leverages a Convolutional Neural Network (CNN) model, specifically designed for rice leaf disease classification. The CNN architecture is customized to focus on rice leaf images, effectively extracting relevant features to distinguish between various disease types. This targeted approach enables more precise classification, contributing to timely and accurate disease management.

The proposed model achieved a notable accuracy of 95.6% during the final epoch of training, indicating its strong predictive capabilities. The model demonstrated low loss, signifying minimal error in its predictions, and exhibited minimal overfitting, ensuring that it generalizes well to unseen data. This performance is highly competitive when compared to existing models. To further evaluate the effectiveness of the proposed CNN model, a comparative analysis was conducted against Transfer Learning-based models, specifically VGG-16 Net and VGG-19 Net. These models are well-regarded for their performance in image classification tasks, yet the customized CNN outperformed both in terms of accuracy and overall efficiency. The specialized nature of the CNN, tailored for rice leaf disease classification, allowed it to achieve superior results.

Keywords: ***Rice crop, Leaf disease, disease prediction, Precision agricultural, transfer learning and convolutional neural networks.***

I. INTRODUCTION

With agriculture serving as their major source of subsistence, more than 80 percent of the Indian population is dependent on agriculture. [1] It is a significant economic engine because it employs 52 percent of the workforce and contributes 15 percent to the growth of the GDP. Nevertheless, we are conscious of the agricultural crisis in the country as well as the lack of direction and investment in the sector. When it comes to the amount of agricultural produce that India produces, plant diseases constitute a significant obstacle. Plant diseases are responsible for ten to sixteen percent of the annual losses that occur in the agricultural sector [2]. For the identification of illnesses, on the other hand, we in India rely on a conventional system that is both more time-consuming and requires the expertise of professional medical professionals. Recently, there has been a rise in the utilization of machine learning (ML) and deep learning (DL) techniques in a variety of practical applications, particularly for the purpose of categorization and object recognition [3].

The cultivation of rice, which is an essential crop in India, is beneficial to the business sector of the country. They believe that the quality will be affected by a variety of factors, including fungi, germs, vaginal stains and burns, leaf burns, and more factors. An interruption has occurred in the production of rice, as well as in its quantity and quality. Agriculturalists face difficulties when it comes to diagnosing ailments. It is possible for image processing techniques to predict the quality of rice in relation to diseases by examining the characteristics of the associated images. A wide variety of classifiers, including decision trees, neural networks, support vector machines, and others, are utilized in the process of disease identification feature classification [4]. When it comes to image processing, deep learning algorithms are competitive with their more traditional counterparts in a variety of different settings. As a result, the objective of this research was to investigate the potential of deep learning models for the prediction and categorization of illnesses in rice.

Researchers have shown a significant amount of interest in deep learning approaches due to the outstanding performance that these approaches have demonstrated in the classification of images. Deep Convolutional Neural Networks, also known as CNNs, are the deep learning technique that is utilized almost exclusively for the purpose of image classification [5]. There are several different deep learning systems that could be utilized for the purpose of image classification. A number of illnesses, including brown spot, leaf spot, bacterial blight, and rice plant diseases, are included in the Kaggle dataset. The proposed model makes use of this dataset in order to evaluate how well it can forecast crop damage [6].

There are several different deep learning systems that can be utilized for the purpose of image classification. Rice plants are susceptible to infection from a variety of illnesses. There is a correlation between these issues and the level of efficiency. A fungal disease known as brown spotting is characterized by the most visible symptoms, which include the appearance of multiple large spots on the leaf, which may finally lead to the complete destruction of the leaf [7]. The emergence of minuscule black dots on the leaves is the defining characteristic of a leaf spot phenomenon. There is a possibility that bacterial degradation will result in significant losses [8].

In the beginning, the lesions manifest themselves as bands on the leaf blades that are dampness caused by water. After some time has passed, the bands will become longer, and the sick leaves will eventually dry out. The process of extracting features and constructing nonlinear feature hierarchies is referred to as feature learning extraction. This process takes use of convolutional neural networks (CNNs), which are a subset of deep learning architectures. It is possible to identify and classify diseases that harm rice leaves by employing the method that has been described. This involves identifying and diagnosing rice leaf diseases at an early stage in order to assist farmers in achieving exceptional yields [9].

This research paper is organized as follows: Section II presents a comprehensive review of existing literature and related work in plant leaf disease classification, highlighting recent advancements and challenges in the field. Section III details the proposed methodology for developing a robust rice plant leaf recognition system, describing the model architecture, parameter fine tuning, and feature extraction strategies. Section IV provides an in-depth overview of the benchmark dataset, including its sources, structure, and relevance to disease classification. Section V discusses the experimental setup, results, and analysis, offering insights into model performance, accuracy, and comparative metrics. Finally, Section VI concludes the study by summarizing key findings, implications for agricultural disease management, and potential directions for future research.

II. LITERATURE SURVEY

It is necessary to detect and classify the numerous illnesses that affect rice plants by analyzing the photographs of their leaves in order to solve the problem of rice leaf disease classification. There are diseases that can have a substantial impact on the productivity and quality of rice, which is a staple food for a significant portion of the world's population [10]. Both the early discovery of these diseases and the proper classification of them are essential for the efficient management of diseases and the protection of food supplies. The practical ramifications that this dilemma has in agriculture have brought it to the forefront of public attention. The timely diagnosis of diseases can assist farmers in taking appropriate actions, such as applying targeted treatments, changing irrigation or fertilization, and reducing the spread of diseases, which ultimately contributes to increased crop yields and lower economic losses. In light of this, a substantial amount of research has been proposed and implemented in order to solve such a scenario [11].

By adopting CNN and making use of a fresh Indian dataset that was gathered from rice fields and the internet, the authors of [12] were able to solve the problem of rice leaf disease categorization. It is a Transfer Learning function that is utilized in the process of constructing the proposed model. Through achieving an accuracy rate of 92.46%, the model that was proposed demonstrated its effectiveness in addressing the issue. Utilizing a number of different deep learning strategies, the authors of [13] presented a system that is capable of accurately predicting rice leaf disease diseases. In order to fulfill the requirements of the algorithm, they gathered and processed photos of diseases that affect rice leaf tissue. Following the extraction of features through the utilization of 32 pre-trained models, the authors further utilized several machine learning and ensemble learning classifiers in order to identify the photos that depicted diseases.

In terms of reaching the highest level of accuracy and succeeding in performance measures, the comparison analysis indicated that their proposed strategy surpassed other approaches that were already in use. Rice panicle neck blast, rice false smut, rice leaf blast, and rice stem blast are the four main rice illnesses that are effectively recognized by the method known as RiceNet, which was described by the authors in [14]. RiceNet operates on a two-stage strategy to properly recognize these diseases. In the beginning, the YoloX model was able to identify the affected areas inside the rice photos. Following the detection of these locations, they were obtained in order to create a new dataset consisting of rice disease patches. When it came time to identify the rice disease patches that had been gathered earlier, a Siamese Network was utilized in the subsequent stage. Through the use of comparison analysis, it was proved that the proposed model performed better than alternative detection models. As we moved on to the identification step, the Siamese Network demonstrated an extraordinary level of accuracy, outperforming other models in terms of performance [15]. During the course of the experiments, it became abundantly evident that the RiceNet model that was proposed outperformed the approaches that were already in use. It also possessed advantages such as a rapid detection speed and a minimal weight size for the purpose of identifying rice diseases.

Keypoint detection, hypercolumn deep feature extraction from CNN layers, and classification are the three processes that the authors of [16] proposed as being extremely important. The activations from each of the CNN layers for a particular pixel are contained within a hypercolumn vector. Important image points that draw attention to distinguishing characteristics are referred to as keypoints. As part of the initial phase of the model, keypoints in the image are identified, and hypercolumn features are extracted based on these spots of interest. Experiments with machine learning entail applying classifier algorithms to the features that have been extracted in the subsequent stage. The findings of the evaluation demonstrate that the method that was described in the research is capable of identifying diseases that affect rice leaf. During the evaluation phase, the Random Forest classifier demonstrated remarkable performance when it was applied to hypercolumn deep features.

Two transfer learning algorithms were examined by the authors of [17] for the purpose of diagnosing diseases that affect rice leaf tissue. The initial approach comprises employing the output of a CNN-based model that has already been pre-trained, in addition to incorporating an appropriate classifier. Using the second approach, the lower layers of the pre-trained network are frozen, the weights of the top layers are fine-tuned, and a suitable classifier is incorporated. There are seven different CNN models that are evaluated in this study using these approaches. The results of the simulation reveal the exceptional performance of four particular networks, which achieved a high level of accuracy of one hundred percent and an F1 score of one. Additionally, in comparison to the other models that were evaluated, the proposed method displayed greater accuracy and a shorter amount of time required for training.

For the purpose of accurately predicting rice diseases, the authors of [18] presented a novel method that makes use of intelligent segmentation and a hybrid machine learning-based classification. Preprocessing, segmentation, feature extraction and selection, and classification are some of the processes that are included in the technique when it comes to classification. The first step in the method involves the normalizing of the data through the utilization of the Synthetic Minority Oversampling Technique-based preprocessing. After that, the Modified

Feature Weighted Fuzzy Clustering algorithm is utilized in order to accomplish effective segmentation. For the purpose of improving the performance of the classifier, Principal Component Analysis is used to extract features, and Linear Discriminant Analysis is used to choose features. In the last step, an Enhanced Recurrent Neural Network is combined with a Support Vector Machine (SVM), resulting in the formation of a hybrid classification model that is intended to improve the powers of prediction. A number of measures, including accuracy, recall, precision, timeliness, and F-measure, are utilized in order to evaluate the efficacy of the procedure. The results of the simulation show that the suggested method beat other classifiers in terms of overall performance, which highlights the potential of the proposed method to enhance disease prediction in rice crops.

III. PRECISION RICE DISEASE PRECITION SYSTEMS

We have proposed a Custom Convolutional Neural Network with the intention of reducing the computational complexity and identify the best parameter for the rice disease prediction. The architecture of the Custom CNN is consist of three convolutional layer, three pooling layer, one flatten and one prediction layer, and it is shown in Figure 1. The proposed model consists of following sequence.

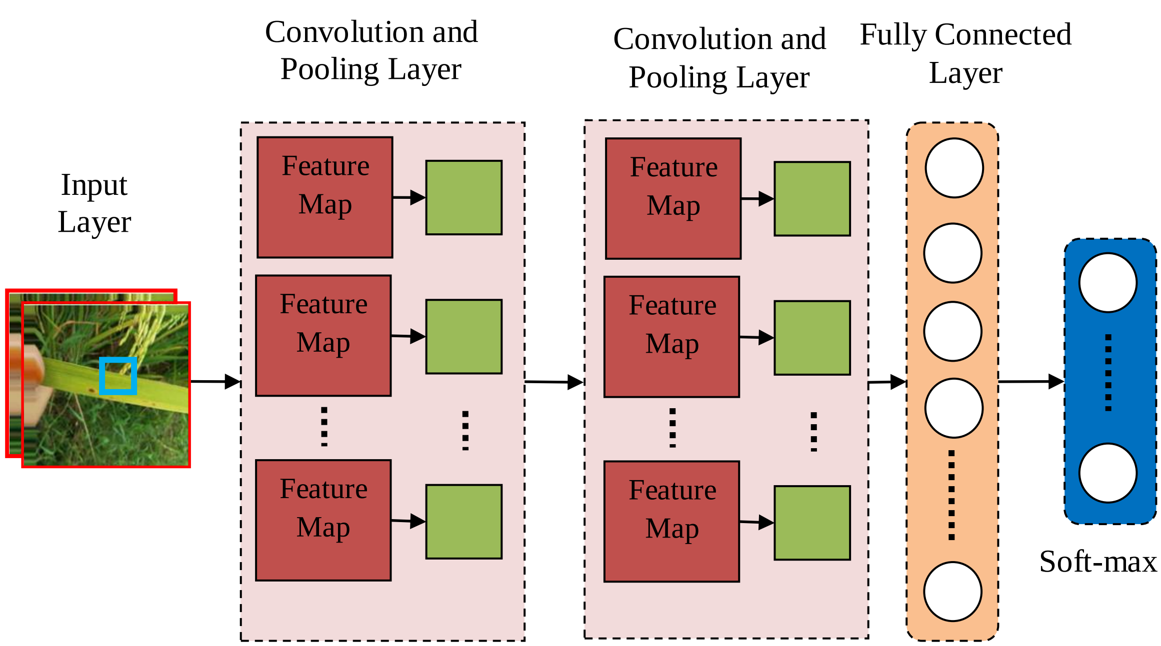

Fig. 1 Architecture of Custom CNN Rice Disease Prediction Model

- Preparing the Dataset
- Rice Disease Prediction Model

- Training the Model
- Evaluation of Performance
- Test Prediction

3.1. Preparing the Dataset

For the purpose of disease identification and classification activities, the Rice Leaf AUG Dataset [19] is a collection of rice leaf images that have been thoroughly collected. A wide range of diseases, including bacterial leaf blight, brown spot, healthy leaf, leaf blast, leaf scald, and narrow brown spot, have been observed on rice leaves, and this collection contains thousands of photos of these diseases. These photographs were taken from a variety of vantage points and under a variety of lighting circumstances in order to portray agricultural settings that are representative of the real world. The total number of rice leaf images is 3,900, and they are divided into six distinct groups, with 650 images in each category.

Fig. 2 Dataset collection for Rice Disease

Each picture has a resolution of 224 by 224 pixels and is exported as a color image with three channels. Figure 2 presents a number of instances, each of which is a rice illness image taken from the Kaggle repository dataset. A test set, a validation set, and a training set were each created from the data set that was initially collected. Eighty percent of the dataset is used to train the model, ten percent is used to validate the model, and ten percent is used to test the model, as shown in Table 1.

Table 1 Rice Disease Dataset splitting ratio

S. No.	Rice Disease Class	Training	Validation	Testing	Total
1.	Bacterial Leaf Blight	520	65	65	650
2.	Brown Spot	520	65	65	650
3.	Healthy Rice Leaf	520	65	65	650
4.	Leaf Blast	520	65	65	650
5.	Leaf scald	520	65	65	650
6	Sheath Blight	520	65	65	650

3.2. Rice Disease Prediction Model

The structural design of the proposed custom CNN model was specifically developed to systematically extract hierarchical characteristics from input images of rice disease leaves. The architecture comprises the subsequent layers:

- Input Layer
- Convolutional Layer
- Max pooling Layer
- Flatten Layer
- Soft-max Classifier

Input Layer: The CNN network begins with an input layer that is capable of accepting images of a standard size, which is typically 224 pixels by 224 pixels.

Convolutional Layers: The custom CNN model is made up of a stack of convolutional layers. Small 3x3 convolutional filters with a stride of 1 are utilized in these layers. A reduction in the spatial dimensions is achieved by interspersing the convolutional layers with max-pooling layers that make use of 2x2 windows and a stride of 2.

$$y_{ij}^{(k)} = \sum_{m=1}^{M} \sum_{n=1}^{N} x_{(i+m)(j+n)} \cdot w_{mn}^{(k)} + b^{(k)} \tag{1}$$

Layer Depth: The total number of layers in CNN is 5, with three of those layers being convolution layers. The convolution layers are intended to extract features that are progressively more complicated as one move deeper into the network.

Filter Sizes and Strides: The first layer uses 64 filters, then 32 filters, and then 32 filters in the subsequent levels. In order for CNN to be able to capture fine details while yet maintaining a relatively modest receptive field, the 3x3 filter size is an important architectural choice.

Activation Function: Rectified Linear Unit (ReLU) activation functions are used after each convolutional and fully connected layer in the neural network. Non-linearity is introduced via ReLU, which also speeds up the training process.

$$y_{ij} = \max\{x_{(p,q)} | p, q \in \text{pooling window}\} \tag{2}$$

Fully Connected Layers: CNN culminates with two fully connected layers, each comprising 4,096 neurons and 2048 neurons, followed by the output layer.

Dropout: In order to prevent overfitting, dropout layers are sometimes inserted before the first two layers that are fully coupled.

Output Layer: The last layer is often a softmax layer, which generates class probabilities for the purpose of image classification.

$$\text{Softmax}(z_i) = \frac{e^{z_i}}{\sum_j e^{z_j}} \tag{3}$$

3.3. Training the Model

The customized CNN model was compiled by using Adam optimizer with learning rate lr is 0.001. The model parameters are identified the best parameters by using the particle swarm optimization techniques. When it comes to evaluation, accuracy is the most important metric. In order to validate the model, it is first trained on the training dataset, and then confirmed using the validation dataset. In order to avoid overfitting, training is carried out for a predetermined number of epochs, and premature termination is determined by the validation loss. It is specified in Table 1 that the parameters that were employed during the training of the model.

Table 2 Model Training Parameters

S. No.	Parameters	Value
1.	Batch Size	32
2.	Learning Rate (lr)	0.001
3.	Evaluation Metrics	Accuracy
4.	Training Dataset	3120
5.	Validation Dataset	390
6	No. of Epochs	20
7	Loss Function	Categorical Cross-Entropy
8.	Early Stopping	Based on Validation Loss

3.4. Evaluation of Performance

There is a diverse selection of possible evaluation metrics for the AD diseases identification and classification that are now under discussion. The metrics of accuracy, precision, recall, and F-measure were investigated during the course of this research and the conclusions were compared with one another. As shown in Figure 6, the evaluation of techniques has to take into consideration four variables: T_P, T_N, F_P, and F_N. When an actual class has been successfully identified, there are only two classes that may exist, and those are T_P and T_N. (TP and TN). In the event that an action is misclassified, it has the potential to fit into either the F_P or F_N category.

	P	N
Y	True Positive	False Positive
N	False Negative	True Negative
	P	N

Fig. 3 working calculations of confusion matrix

Precision: When determining how far a metric will operate, precision is one of the most popular techniques to quantify the effectiveness of the metric. This allows us to determine the accuracy of our measurements.

$$\text{Precision} = \frac{t\_p}{t\_n + t\_n} \quad (4)$$

Recall: Recall is the number of events that could be correctly predicted out of the total number of events.

$$\text{Recall} = \frac{t\_p}{f\_n} \qquad (5)$$

Accuracy: The accuracy can be measured by looking at the percentage of instances that were accurately labeled. The percentage of correct classifications relative to the total number of classifications is the accuracy metric for a classification system.

$$\text{Accuracy} = \frac{t\_p+t\_n}{t\_p+t\_n+f\_n+f\_p} \qquad (6)$$

F1-Score: The harmonic mean is indicated by the score F1, which may be found among the other possible F scores.

$$\text{F1} = \frac{t\_p+t\_n}{t\_p+t\_n+f\_n+f\_p} \qquad (7)$$

3.5. Test Prediction

The proposed model was trained and tested with benchmark Rice Leaf AUG dataset using tensor flow in Core i7 CPU 2.6GHz, 1 TB of Hard Disk and 16 GB of RAM. The proposed custom CNN model, experimental results are performed using different parameters like batch size, learning rate, loss of entropy, number of epochs, accuracy and early stopping.

IV. EXPERIMENTAL RESULTS AND DISCUSSIONS

The results that were achieved by the model that was constructed over the course of a number of various experimental scenarios are discussed in this section. Next, arguments and comparisons are presented in response to these findings. Additionally, Python and the Keras deep learning framework were utilized and utilized in the development of the aforementioned model. Google Colab was used to run each and every simulation, and a 12GB NVIDIA Tesla K80 GPU was used overall. Python was also used to generate the model before it was used. The experimental design is comprised of the datasets, and then the performance of each dataset is analyzed separately. Through a process of trial and error, each of the parameters is defined, and the findings are summarized with the values that are deemed to be optimal for the parameters once they have been determined.

4.1. Result and Discussions

To evaluate the effectiveness of custom CNN model for rice leaf disease classification, we have to conducted experiments on benchmark Rice Leaf AUG dataset. The dataset contains different rice leaf disease information. The experimental setting of custom CNN model consists of three convolutional layer and max pooling. For avoiding the problem of overfitting concepts, we have used dropout and Adam optimizers. The sample rice leaf disease sample prediction results are shown in Figure 4.

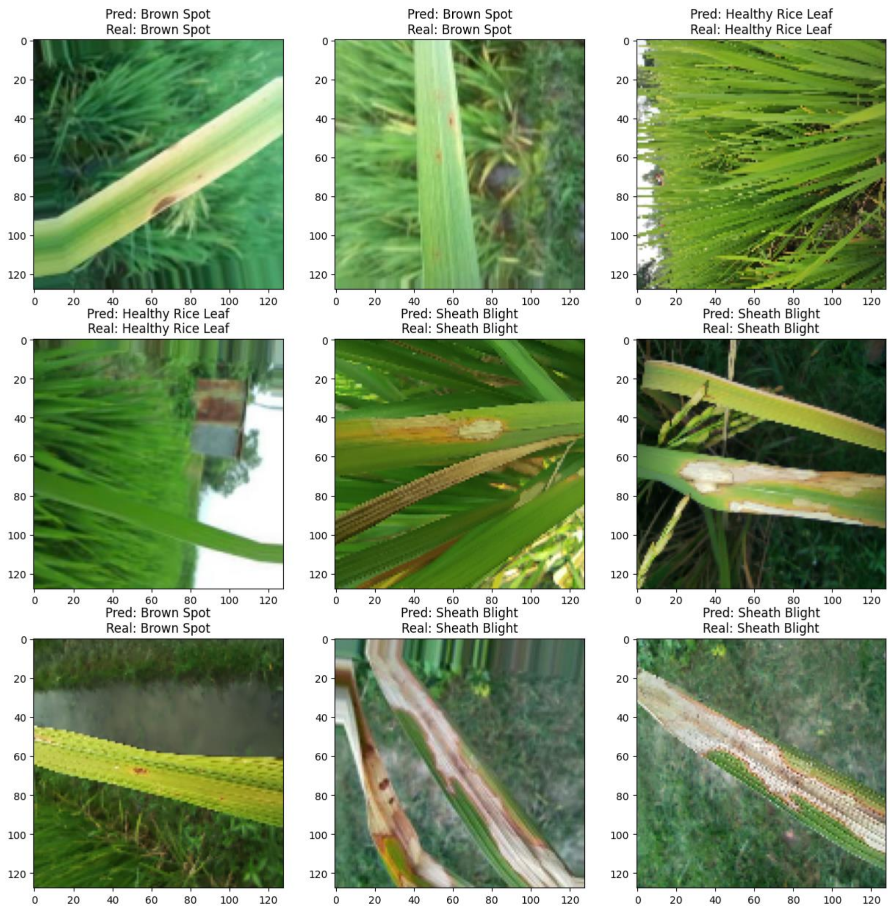

Fig. 4 Maize crop pest control system

In this CNN model tailored for rice leaf disease detection, trainable parameters like convolutional filters and fully connected layer weights dynamically adjust during training, fine-tuning the model's ability to extract disease-specific features and boost classification accuracy. The non-trainable parameters such as the batch normalization layer's moving statistics or frozen layers in comparative transfer learning models remain fixed, providing a stabilizing effect that aids in consistent learning and computational efficiency. The trainable, non-trainable and optimized parameters are shown in Figure 5.

Layer (type)	Output Shape	Param #
rescaling (Rescaling)	(None, 224, 224, 3)	0
conv2d (Conv2D)	(None, 222, 222, 64)	1,792
max_pooling2d (MaxPooling2D)	(None, 111, 111, 64)	0
conv2d_1 (Conv2D)	(None, 109, 109, 32)	18,464
max_pooling2d_1 (MaxPooling2D)	(None, 54, 54, 32)	0
conv2d_2 (Conv2D)	(None, 52, 52, 32)	9,248
max_pooling2d_2 (MaxPooling2D)	(None, 26, 26, 32)	0
flatten (Flatten)	(None, 21632)	0
dense (Dense)	(None, 512)	11,076,096
dense_1 (Dense)	(None, 6)	3,078

Total params: 33,326,036 (127.13 MB)
Trainable params: 11,108,678 (42.38 MB)
Non-trainable params: 0 (0.00 B)
Optimizer params: 22,217,358 (84.75 MB)

Fig. 5 Trainable, non-trainable and optimizer parameters for Rice leaf disease

Figure 6 presents a detailed comparison of training and validation accuracy, as well as training and validation loss, for the Rice Leaf AUG dataset over a span of 20 epochs, allowing an assessment of model learning progress and potential overfitting.

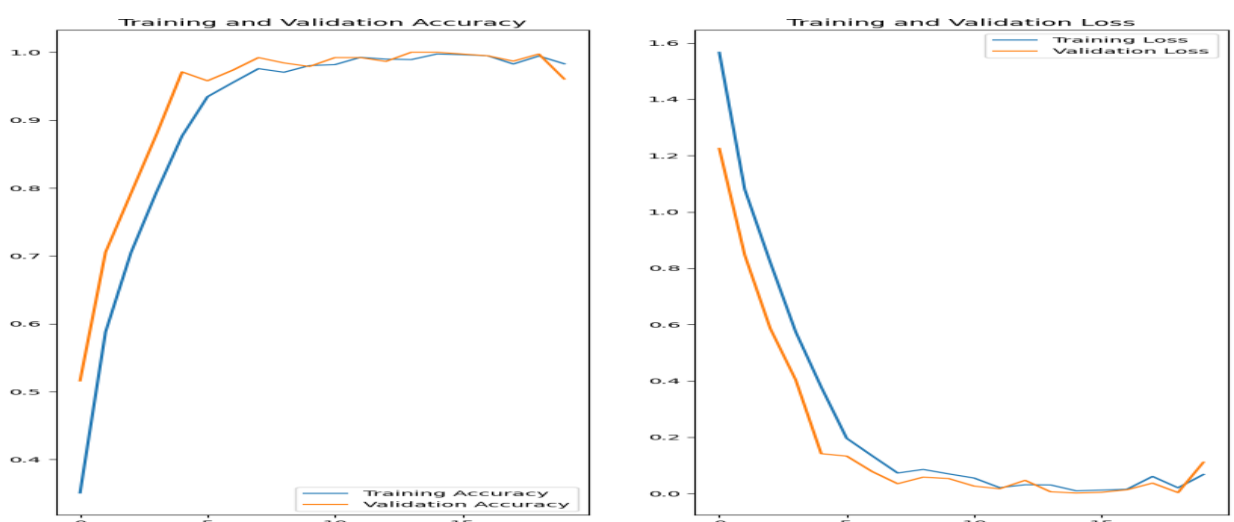

Fig. 6 Training, validation accuracy and loss of rice leaf disease system

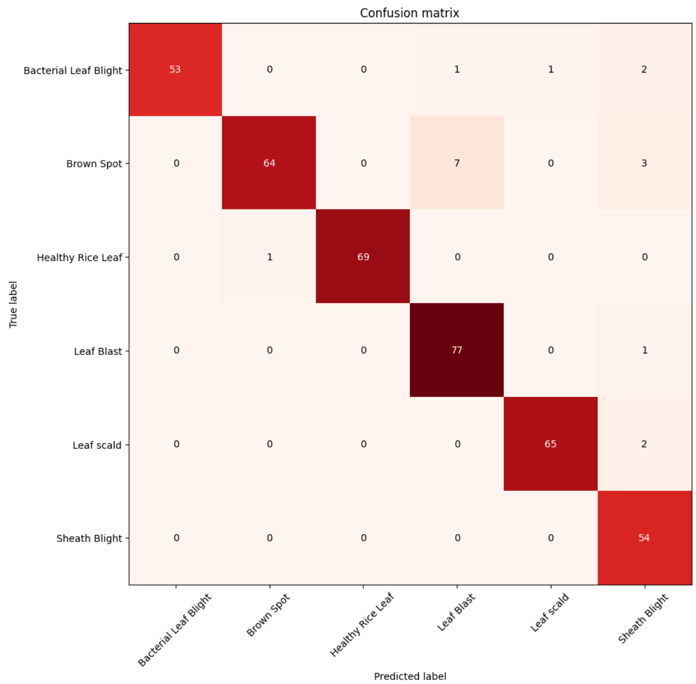

Fig. 7 Confusion matrix of proposed rice leaf disease system

Figure 7 provides the confusion matrix of the proposed custom CNN model, visually illustrating the classification performance across different rice leaf disease classes, including true positive, false positive, and false negative rates. In Figure 8, the performance metrics for each individual rice leaf disease category are broken down, highlighting the model's precision, recall, and F1-score for each class, offering deeper insights into classification effectiveness and areas for potential model improvement.

	precision	recall	f1-score	support
Bacterial Leaf Blight	1.00	0.93	0.96	57
Brown Spot	0.98	0.86	0.92	74
Healthy Rice Leaf	1.00	0.99	0.99	70
Leaf Blast	0.91	0.99	0.94	78
Leaf scald	0.98	0.97	0.98	67
Sheath Blight	0.87	1.00	0.93	54
accuracy			0.95	400
macro avg	0.96	0.96	0.96	400
weighted avg	0.96	0.95	0.96	400

Fig. 8 Performance analysis of proposed rice leaf disease system

V. CONCLUSION

This study presents a highly effective and tailored approach to rice leaf disease detection, employing a customized Convolutional Neural Network (CNN) model optimized for precise feature extraction from rice leaf images. Achieving an impressive accuracy of 95.6% and demonstrating low error rates with minimal overfitting, the model provides a reliable solution for early disease identification, which is crucial for crop health and sustainable agriculture. The CNN's performance surpasses that of established Transfer Learning models like VGG-16 and VGG-19, underscoring the value of a specialized model in achieving superior classification accuracy and efficiency in rice leaf disease management. This approach holds significant promise for real-world applications, where timely and accurate disease diagnosis is essential for protecting yield, supporting food security, and contributing to economic stability in agricultural sectors.

In Future enhancements, it could include integrating IoT devices for real-time monitoring, expanding the model for multi-class disease classification and severity estimation, exploring hybrid and ensemble learning approaches, applying advanced architectures like EfficientNet for improved accuracy, adapting the model for cross-crop disease detection, and developing a user-friendly mobile or web application for accessible, on-site disease detection.

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