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Enhancing Rice Crop Management: Disease Classification Using Convolutional Neural Networks and Mobile Application Integration

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Abstract: Early diagnosis of rice disease is important because it poses a considerable threat to agricultural productivity as well as the global food security of the world. It is challenging to obtain more reliable outcomes based on the percentage of RGB value using image processing outcomes for rice disease detections and classifications in the agricultural field. Machine learning, especially with a Convolutional Neural Network (CNN), is a great tool to overcome this problem. But the utilization of deep learning techniques often necessitates high-performance computing devices, costly GPUs and extensive machine infrastructure. As a result, this significantly raises the overall expenses for users. Therefore, the demand for smaller CNN models becomes particularly pronounced, especially in embedded systems, robotics and mobile applications. These domains require real-time performance and minimal computational overhead, making smaller CNN models highly desirable due to their lower computational cost. This paper introduces a novel CNN architecture which is comparatively small in size and promising in performance to predict rice leaf disease with moderate accuracy and lower time complexity. The CNN network is trained with processed images. The image processing is performed using segmentation and k-means clustering to remove background and green parts of affected images. This technique proposes to detect rice disease of rice brown spot, rice bacterial blight and leaf smut with reliable outcomes in disease classifications. The model is trained using an augmented dataset of 2700 images (60% data) and validated with 1200 images of disease-affected samples to identify rice disease in agricultural fields. The model is tested with 630 images (14% data); testing accuracy is 97.9%. The model is exported into a mobile application to introduce the real-life application of the outcome of this work. The model accuracy is compared to others work associated with this type of problem. It is found that the performance of the model and the application are satisfactory compared to other works related to this work. The over-all accuracy is notable, showing the reliability and dependability of this model to classify rice leaf diseases.

Keywords: image processing; CNN model; K-means clustering; disease classification



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1. Introduction

The demand for food items like rice is increasing day by day due to the growing population all over the world. Almost 23% of people get most of their calories from rice [1]. Considering its impacts in global nutrition, it holds significant importance among the multitude of crops available all over the world. The effective management of rice diseases can increase the production of rice in agricultural innovations.

Multiple diseases affecting rice, such as viral, bacterial and fungal effects degrade the quality and quantity of rice which creates major problems for the global economy. It is important to identify paddy disease very early for proper management and treatment in the agricultural field. Due to the viral, bacterial and fungal effects, a variety of rice diseases, namely, bacterial blight, rice brown spot, rice blast and leaf smut are seen in paddy fields [2]. Each disease has a particular color, shape and pattern of affected portions on leaves. Rice bacterial blight shows water-soaked stripes on leaf edges, yellow or white stripes on leaf edges [3]. Brown spots can be identified from a distance by their brownish scorched appearance on the leaves.

Though manual monitoring can indicate disease, it is tedious and erroneous for large fields [4]. In order to initiate disease treatment, individuals are required to bring the disease sample to specialists and await further instructions which is time-consuming and costly in agricultural field management [5,6].

In this case, researchers concentrate on detecting plant disease through image processing instead of manual observations [7]. Various image-processing approaches have been employed for disease management in the agricultural field. It is quite challenging to detect rice disease at an early stage properly based on colors, spots or streaks on leaves or stems using image processing techniques [8–10].

Therefore, a Convolutional Neural Network (CNN) is incorporated with pre-processing of images to get reliable outcomes in rice disease detections and classifications [11]. CNNs are used for the classification of datasets with proper feature extractions. Segmentation, thresholding and clustering are used to analyze the color, shape and pattern of affected spots on leaves in rice disease classifications [12].

So, the overall task involves a series of objectives related to rice leaf disease classification. Firstly, an image processing technique is applied to extract the diseased portions from rice leaf images. This step allows for targeted analysis and identification of the affected areas. Next, a Convolutional Neural Network (CNN) is constructed, which is trained and utilized for the purpose of classification. The CNN is fine-tuned by adjusting various parameters and modifying layers to achieve optimal performance in disease identification. Subsequently, the model is tested using rice leaf disease images and its accuracy is compared against known data. Lastly, the model is integrated into an Android-based smartphone application, enabling real-time detection of rice leaf diseases. This comprehensive approach aims to enhance the identification and management of rice leaf diseases through advanced image processing techniques and machine learning algorithms.

A literature review, a study of related papers, is discussed in Section 2. Section 3 contains the methodology we have used for our work. The result and discussion are given in Section 4. Section 5 explains how the trained model has been plugged into a mobile application. The conclusion and probable future work are highlighted in Section 7.

2. Literature Review

Stephen et al. [13] used CNN architectures for the identification of healthy and diseased leaves. The researchers applied self-attention with ResNet34 and ResNet18 for the improvement of feature selection and avoided gradient problems by using ResNet50 and ResNet34. They suggested that self-attention with ResNet34 achieved 98.54% average accuracy in multiclass classification.

The authors of [14] reviewed ML and AI methods for the detailed identification of rice diseases. As rice is an economically important food crop all across the globe, they focused on deep learning, machine learning and AI tools for recognizing rice diseases.

The authors of [15] detected paddy leaf disease by using faster region-based CNN (Faster R-CNN) in real-time. It was proposed that if the regional proposal network (RPN) was faster the efficiency of the R-CNN was increased. The candidate regions were generated because RPN can locate the location of the targeted object in a precise way. They used already available datasets and also produced their own. They combined 650 healthy leaf images, 600 rice blast images, 650 brown spots and 500 hispa images, and produced a

total dataset of 2400 images. By concentrating on 2230, 11 and 2022 plants, and 4 of 17 on rice blast, brown spot, and hispa classes, the authors recorded 98.09%, 98.85% and 99.17% accuracy, respectively. They identified healthy rice leaves with 99.25% average accuracy.

To classify the rice grains, the authors of [16] proposed the use of a CNN for image-based datasets and a Deep Neural Network (DNN) or ANN for feature-based datasets. No specific rice diseases were targeted in this study because the researchers focused on different types of rice grains for the detection of healthy leaves. They collected 15,000 photographs of five types of rice grains: Arborio, Basmati, Ipsala, Jasmine and Karacadag and finally collected 75,000 images in total. After extracting 106 features from these images, they produced a feature-based dataset including morphological, four-shape and color features. According to the findings, the average grain classification for ANN was reported as 99.87%, while DNN achieved a classification rate of 99.95% and CNN demonstrated a perfect classification rate of 100%.

The authors of [17] introduced a new CNNIR-OWELM-based algorithm for the categorization of paddy diseases by combining optimal weighted extreme learning machines (WELM) and Residual Network (ResNet) v2 based on CNN. This system combined IoT for segmenting the infected areas through histogram segmentation and capturing images, followed by the use of deep learning inception (ResNet v2) for the extraction of features.

The authors of [18] used a freely accessible dataset and produced 3500 images of diseased and healthy paddy leaves. They introduced the researchers to highly efficient crop care systems by using a Convolutional Neural Network compared to other models. This study suggested a very fast solution to classifying healthy and diseased crops by locating the affected areas of plants. They obtained 70% accuracy by creating a classification module with CNN and building the model for 1–10 epochs. For eight epochs, 72.17% of the validation accuracy was achieved.

The researchers of [19] generated ensemble models for the classification of various kinds of diseases such as brown spot, bacterial stripe disease, sheath blight, false smut and leaf blast. The findings of the study achieved 91% overall accuracy.

Feng et al. [20] detected paddy leaf diseases by employing hyperspectral imaging (HIS) and generated CNN architectures by using deep transfer learning techniques. The results of the study indicated that fine-tuning was an efficient solution that provided 88% accuracy.

Upadhyay et al. [21] identified and classified rice plant diseases by analyzing the size, color and shape of lesions present on leaf images using the CNN method, and achieved 99.7% accuracy on the dataset.

Chen et al. [22] presented the BLSNet strategy, which could identify and detect the damage to leaves caused by Bacterial Leaf Streak (BLS) disease. This disease affects the quantity and quality of rice growth. In a comparative analysis with other benchmark models, BLSNet exhibited superior performance in accurately detecting and identifying damage and its level of severity.

The authors of [23] used color features for the classification of paddy diseases. The researchers extracted a total of 172 features from each channel after analyzing 14 color spaces. A dataset of 619 images belonging to four classes (sheath blight, healthy leaves, bacterial leaf blight and rice blast) was used. For testing their methodology, they used different classifiers, including discriminant classifiers (DCs), SVM, K-NN, NB, DT, Random Forest (RF) and LR; 94.65% of the SVM's highest accuracy was reported.

The researchers of [24] built a system by integrating machine learning (ML) and image processing technologies. For the identification of plant diseases, they developed an application that also predicts the amount of fertilizer to be used for diseased crops. They produced a dataset of 1000 images (for three diseases) and separated them into different folders according to the type of disease. Image processing techniques were used for obtaining their relevant features and creating two different classification models: Back Propagation Neural Network (BPNN) and Support Vector Machine (SVM).

Chen et al. [25] achieved impressive bed disease classification and image processing through deep learning techniques. They achieved 94.07% overall accuracy on the public

dataset and 98.63% on rice disease image classification by combining the Inception and DenseNet modules.

To categorize the rice crop diseases: false smuts, bacterial leaf blight and brown spots [26], it was proposed by the authors to use a Support Vector Machine (SVM) classifier. They also proposed that Bag of Word (BoW) and Scale-Invariant Feature Transform (SIFT) should be used for extracting the features. Moreover, after the SVM classifier, the use of Brute-Force (BF) matchers and K-means clustering was proposed. A dataset comprising 400 images was used, which belonged to different sources: Rice Research Institute (RRI), Rice Knowledge Bank (RKB) and the American Psychopathological Society (APS). The researchers indicated 90.9% precision, 91.6% recall and 94.16% average accuracy, but the dataset was very small because the SVM classifier is susceptible to overfitting regarding multiclass classification.

The authors of [27] reviewed image processing techniques and provided an outline to classify and detect plant diseases. Image processing techniques can help in the detection of leaf diseases at an early phase and they can be controlled to prevent them from spreading further. The researchers indicated that color co-occurrence, Neural Network and K-means clustering may be employed to identify and categorize plant diseases.

T. Islam et al. [28] recommended an approach with color feature to identify rice diseases, namely, rice blight and rice black spots. They extracted RGB values of impacted portions of leaves using a naive Bayesian classifier. They achieved over 89% categorization reliability for rice disease detection and classifications considering the percentage of the RGB affected area as a feature in their work.

Phadikar and Goswami [29] employed image processing to identify rice blast and rice brown spot in the agricultural field. They considered noise removal and segmentation criteria to get better performance in disease detection techniques. They obtained only 84% accuracy with five features of homogeneity, contrast, correlation, energy and entropy for disease classification through image processing.

Joshi and Jadhav [30] proposed a model to detect rice disease, namely, rice blast, rice bacterial blight, rice brown spot and rice sheath rot. They used the Minimum Distance Classifier (MDC) and K-Nearest Neighbor classifier (K-NN) to extract features of like shape and color in their model. They obtained 89.23% classification accuracy with the steps of pre-processing and segmentation in their model.

Qiu et al. [31] employed a deep convolutional network to construct a paddy disease identification model. They utilized the Keras deep learning architecture for training and explored various convolution kernel sizes and pooling functions to investigate the classification and recognition of three different rice diseases. Impressively, their model achieved an accuracy exceeding 90%.

Krishnamoorthy et al. [32] introduced an innovative transfer learning approach using the InceptionResNetV2 model. They effectively combined feature weights and fine-tuned hyperparameters to accurately identify three distinct rice diseases, achieving recognition accuracy of 95.67%.

In reference [33] the authors aimed to enhance the accuracy of rice disease diagnosis using VGG-16 and GoogLeNet models. These models were trained on a dataset comprising three distinct species of painless diseases. The experimental results demonstrated that the average classification accuracies achieved by GoogLeNet and VGG-16 were 91.28% and 92.24%, respectively.

Early and accurate recognition of plant diseases is crucial for safeguarding grain production. Vimal K. Shrivastava et al. [34] addressed the limitations of traditional plant disease detection systems. Their study involved four classes, including three disease categories and one class for healthy leaves. To accomplish this, they leveraged a pre-trained deep CNN model, namely AlexNet, along with an SVM classifier and transfer learning techniques. Impressively, their approach yielded an accuracy of 91.37% in disease classification.

Dengshan Li et al. [35] introduced an innovative mechanism for real-time rice leaf disease detection using deep learning techniques. Their approach involved employing

faster-RCNN for image detection from video streams. Additionally, they explored several deep CNN models, including YOLOv3, ResNet-101, ResNet-50 and VGG16, to enhance the accuracy and performance of their detection system.

According to the literature review, it was revealed that researchers have used different classifiers for rice disease detection and classifications through image processing. They obtained 80~99% classification accuracy with different classification algorithms such as SVM, Naive Bayes Classifier, K-NN MDC, etc. They achieved faster and non-invasive criteria in rice disease detections considering the RGB percentage of the affected leaves. It is quite challenging to achieve more reliable outcomes based on the color features in image processing. Therefore, the proposed model incorporates K-means clustering with CNN techniques to obtain more reliable outcomes in agricultural innovations. There are hardly any models with a trade-off between the accuracy and size of the network. A smaller CNN network with lower run time and space can be designed to keep significant accuracy considering the use of the network in mobile applications.

3. Methodology

Total research work has been divided into three phases, image acquisition, image pre-processing and image classification with CNN model. The proposed model includes several pre-processing steps and the training a designed CNN model to classify rice leaf diseases as shown in Figure 1. In the pre-processing steps, there are criteria of thresholding and K-means clustering for background removal and extraction of the diseased portion from the image.

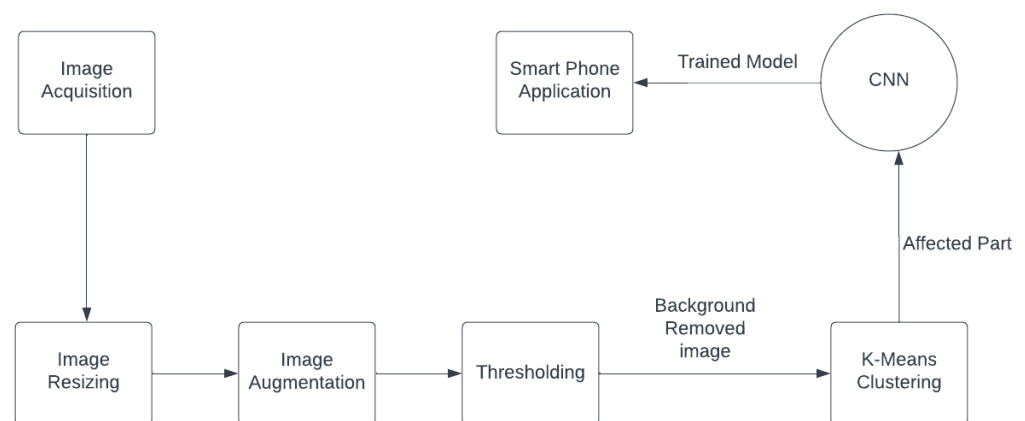


Figure 1. Sequential steps of overall work.

3.1. Image Acquisition

Dataset of rice leaf diseases has been collected from Kaggle to carry out the analysis of the proposed model. A dataset comprising 2700 augmented RGB images depicting three distinct diseases, namely, bacterial leaf blight, brown spot and leaf smut, was utilized to train a disease classification model. Table 1 presents the detail information about the dataset. According to Figure 2, 59.6% data are used from total dataset of affected leaves for training of the model where 13.9% data are used for testing of the model. For increasing the instances, the dataset has been augmented. The partitioning of dataset is shown in Figure 2.

Table 1. Number of images in different classes for training, testing and validation.

Class	Training Instances	Validation Instances	Testing Instances
Bacterial leaf blight	900	400	210
Brown spot	900	400	210
Leaf smut	900	400	210

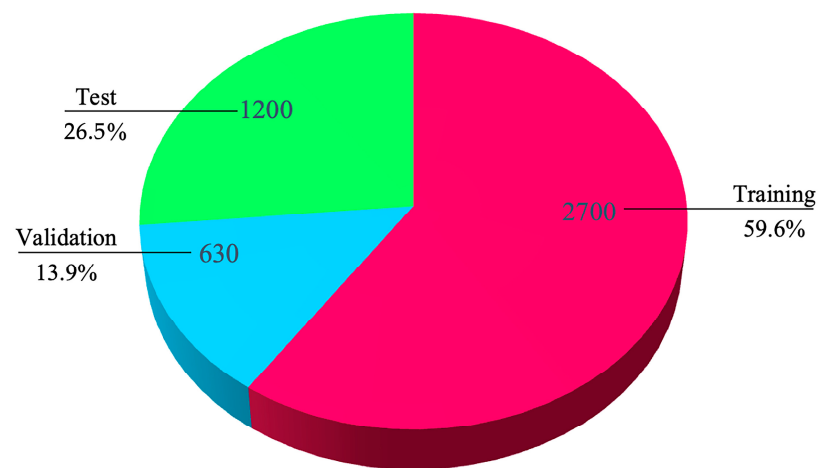


Figure 2. Partitioning of data for training, testing and validation purposes.

3.2. Image Pre-Processing

Thresholding and clustering were included in image pre-processing as removal of the background and unnecessary areas of the image. We use the color transforming model in image processing according to Equation (1).

$$g(x, y) = T[f(x, y)] \quad (1)$$

Here, $f(x, y)$ represents the input color image; transformed output color image is $g(x, y)$. To improve the intensity of the color image, Equation (2) was used in the HSV color space.

$$g(x, y) = kf(x, y) \quad (2)$$

The algorithm to convert RGB image to HSV image is below.

1. Three channels, R, G and B, are extracted from the image.
2. The following terms are calculated:

$$R' = \frac{R}{255} \quad (3)$$

$$G' = \frac{G}{255} \quad (4)$$

$$B' = \frac{B}{255} \quad (5)$$

3. The difference Δ is calculated from c_{max} and c_{min} :

$$C_{max} = \max(R', G', B') \quad (6)$$

$$C_{min} = \min(R', G', B') \quad (7)$$

$$\Delta = C_{max} - C_{min} \quad (8)$$

4. Calculation of Hue is:

$$H = 60^\circ \times \left(\frac{G' - B'}{\Delta} \right) \bmod(6) \text{ if } C_{max} = R' \quad (9)$$

$$H = 60^\circ \times \left(\frac{B' - R'}{\Delta} + 2 \right) \text{ if } C_{max} = G' \quad (10)$$

$$H = 60^\circ \times \left(\frac{R' - G'}{\Delta} + 4 \right) \text{ if } C_{max} = B' \quad (11)$$

$$H = 0^\circ \text{ if } \Delta = 0$$

5. Calculation of Saturation is:

$$S = \begin{cases} \frac{\Delta}{C_{max}}, & C_{max} \neq 0 \\ 0, & C_{max} = 0 \end{cases} \quad (12)$$

6. Calculation of Value is:

$$V = C_{max} \quad (13)$$

The background of resized image was made white to keep uniform size of the images. According to Figure 3, the RGB image was converted to HSV color space so that the S (saturation) channel was extracted in pre-processing of images. HSV color map was used for color-based segmentation.

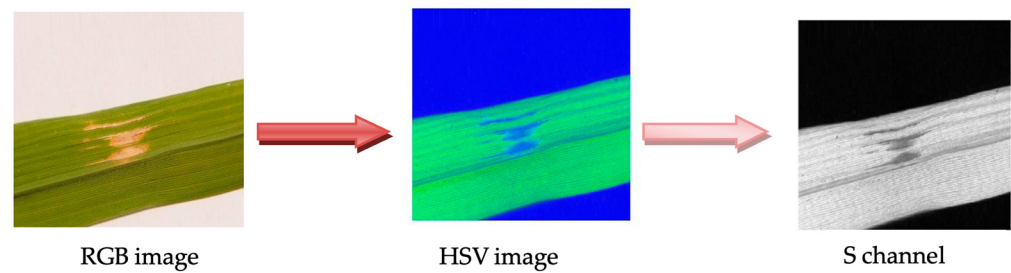


Figure 3. Conversion of RGB image to HSV and S channel.

Histogram of a digital image with number of levels L (0 to $L - 1$) is a discrete function which is defined by:

$$h(k) = n_k \quad (14)$$

where ' k ' is k -th level of the image, n_k is number of times k appears in the image.

Though the non-affected part of the image is green, the elimination of the green part is necessary to stop misleading for the training of the network. For this reason, thresholding was used for obtaining better performance with the advanced K-means clustering technique as shown in the block diagram of Figure 4.

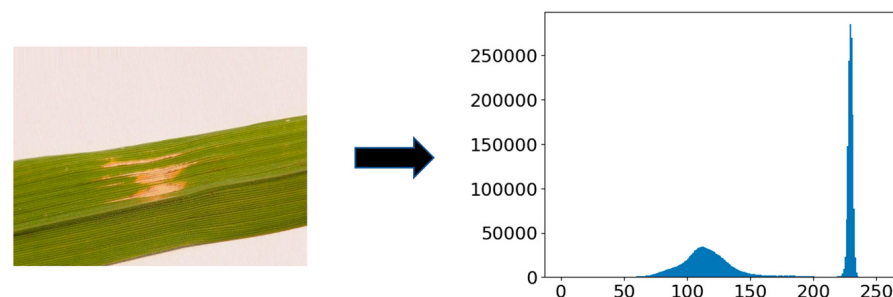


Figure 4. Histogram of saturation(s) channel from affected leaves.

Segmentation of disease-affected area is needed to discard for faster and efficient image processing criteria. After histogram analysis of the S-channel, the threshold value is obtained as shown in Figure 4.

Here, the green pixels that fall within the threshold level are replaced with white pixels and affected pixels are unmodified because green pixels represent an unaffected section of

the leaf that is not required for disease identification and classification. The pixels in the disease-affected area are unaltered using K-means clustering as shown in Figure 5. The outcome of the clustering appears in Figure 6.

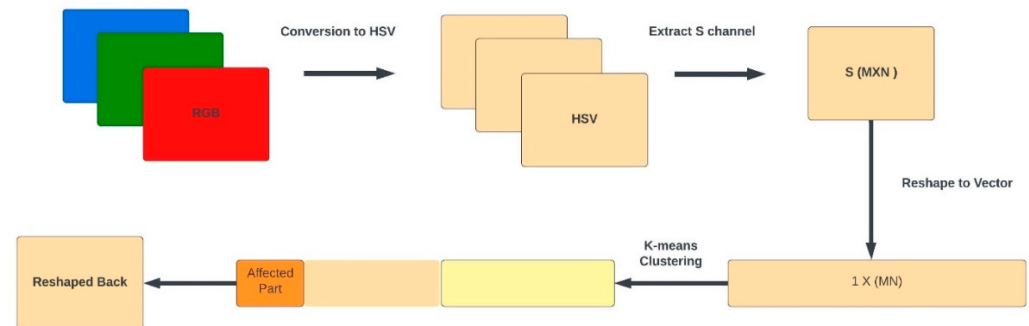


Figure 5. Fundamental block of using k-means clustering to select non-affected part.



Figure 6. Image pre-processing with thresholding and K-means segmentation.

3.3. CNN for Disease Classifications

The Convolutional Neural Network (CNN) was incorporated in the proposed model to extract suitable features for obtaining reliable outcomes in rice disease classifications [36]. CNN model was used after pre-processing of images to get better performance in disease detection model.

Figure 7 shows the flow diagram of the CNN model, where each block symbolizes each step of the work: According to the CNN architecture, it includes convolution, batch normalization, ReLU, pooling layer, a dense network, a soft-max layer and a classification layer in image processing. Forward propagation is used to get the output from the pooling layer. The kernel and weights are revised according to the backpropagation in the CNN model as shown in Figure 7. The last two layers are the soft-max layer and classification layer which classifies and provide the predicted label of the image.

The CNN network has some parameters some of which are trainable and some are non-trainable. The number of parameters tells how much learning capability the network has. It also denotes the computational complexity of the network. The series network with the following parameters detailed in Table 2 is used in our work.

The model was run on Google Collaboratory having a computing environment with the following specifications: It featured two CPUs, each having a single core and 2 threads per core. The clock speed was set at 2.2 GHz and the CPU model employed was Intel(R) Xeon(R). The system had a total of 12 GB of RAM, providing ample memory for processing tasks. In addition, the disk size was 103 GB, ensuring sufficient storage capacity for data and model files. These specifications combined to create a powerful and capable computing environment for running the model on Google Collaboratory.

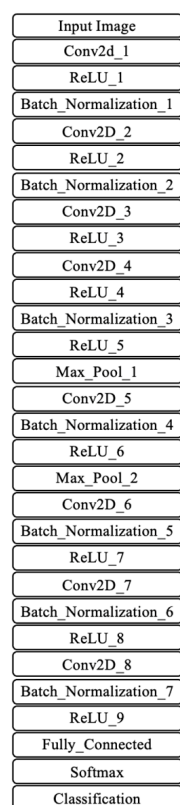


Figure 7. Convolutional Neural Network architecture for the proposed model.

Table 2. No. of parameters employed in CNN network.

Layer Type	Output Shape	No of Parameters
Conv3D	(None, 300, 300, 3, 4)	112
Batch Normalization	(None, 300, 300, 4)	16
Conv2D	(None, 300, 300, 32)	1184
Batch Normalization	(None, 300, 300, 32)	128
Conv2D	(None, 300, 300, 64)	18,496
Conv2D	(None, 300, 300, 64)	36,928
Batch Normalization	(None, 300, 300, 64)	256
Max Pooling 2D	(None, 300, 300, 64)	0
Conv2D	(None, 300, 300, 128)	73,856
Batch Normalization	(None, 300, 300, 128)	512
Max Pooling 2D	(None, 300, 300, 128)	0
Conv2D	(None, 300, 300, 256)	295,168
Batch Normalization	(None, 300, 300, 256)	1024
Conv2D	(None, 300, 300, 512)	1,180,160
Batch Normalization	(None, 300, 300, 512)	2048
Flatten	(None, 300, 300, 512)	0
Dense	(None, 300, 300, 512)	6147
Trainable Parameters: 3,974,875		Non-Trainable Parameters: 3016
		Total: 3,977,891

4. Results and Discussion

According to Figure 8, the activated areas which are actually the affected portions of the leaves are visualized when the background is removed using thresholding criteria in image processing. The pattern, edge and color are extracted as features that are responsible for predicting the class.

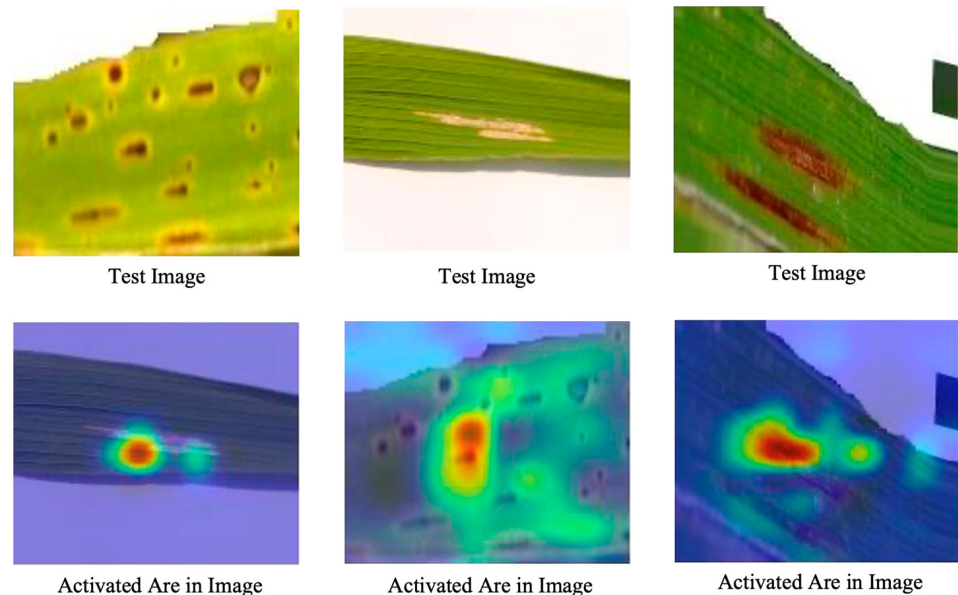


Figure 8. Activated areas of the images for classification of disease.

The dataset was obtained on different rice disease samples including bacterial blight, brown spot and leaf smut. The model was trained using a dataset of 2700 images and validated with 1200 images. The model was tested through 630 images of disease-affected leaves. The training initiates with a learning rate of 0.001 and continues until the validation criteria are fulfilled as shown in Figure 9.

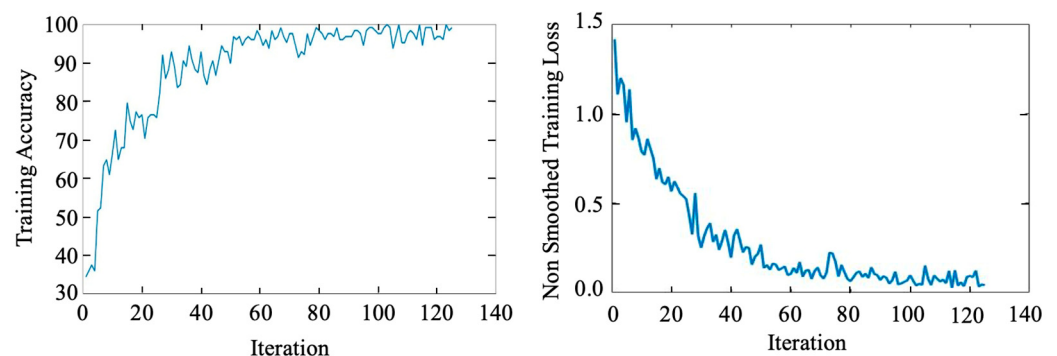


Figure 9. Training progress of the proposed model.

According to Figure 9, training accuracy reaches 1 at or near the 80th iteration while validation accuracy converges after the 130th iteration, alternatively said, after the 5th epoch. The validation accuracy of the progress changes with iteration and reaches around 97.9% after 130 iterations as shown in Figure 10.

Beside our main dataset another dataset with three disease classes was trained and tested for our network. For most cases it provided promising accuracy. Though for dataset-2 with field background behind multiple leaves, it fell below 80% as shown in Table 3. The separating capability of the model, for this case only, is not very reliable as the leaves represented in the image are overlapped and cannot be segmented properly.

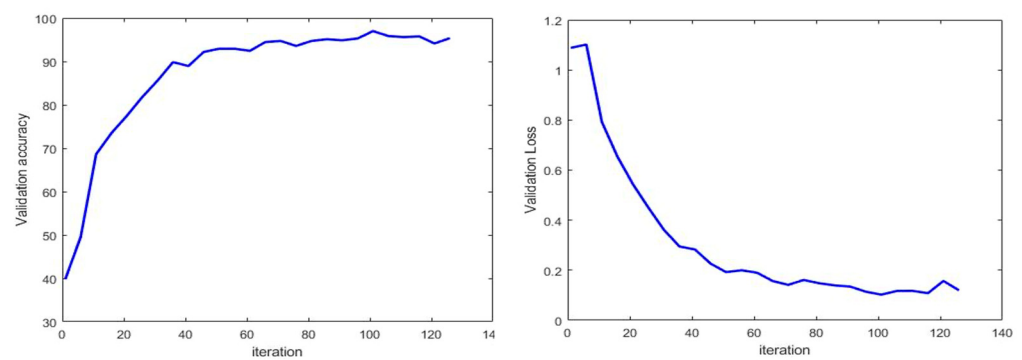


Figure 10. Validation accuracy and loss per iteration.

Table 3. Robustness of proposed model for different dataset.

Dataset		Obtained Accuracy	Description of Dataset
Dataset-1 [37] + Some Local Data		97.9%	Train set has 2700 augmented images with white background, each having single leaf.
Dataset-2 [38]	White Background	88.3%	Train set has 1508 augmented images with white background, each having single leaf. Train set has 690 augmented images with field background, each having multiple leaves.
	Field Background	78.5%	
Dataset-3 [39]		92.7%	Train set has 1000 original images with field background, each having multiple leaves.

After training the model, the confusion matrix was obtained to classify the diseases of bacterial leaf blight, brown spot and leaf smut as shown in Figure 11. According to the confusion matrix in Figure 11, the classification accuracy was seen as 97.9% whereas the error rate was obtained as 2.1% for rice disease classifications.

Confusion Matrix				
Output Class	Bacterial leaf blight	Brown spot	Leaf smut	
	206 32.7%	0 0.0%	6 1.0%	97.2% 2.8%
	4 0.6%	210 33.3%	3 0.5%	96.8% 3.2%
	0 0.0%	0 0.0%	201 31.9%	100% 0.0%
				Target Class
				98.1% 1.9%
				100% 0.0%
				95.7% 4.3%
				97.9% 2.1%

Figure 11. Confusion matrix denoting the test accuracy for each class.

The confusion matrix shows the test accuracy of bacterial leaf blight, brown spot and leaf smut as 97.2%, 96.8% and 100% accuracy as shown in Figure 11 for predicting the disease classes.

The ablation technique was used to determine the effect of two image processing steps by comparing their accuracy for each case. Incorporating these two steps raised accuracy by about 8% as shown in Table 4.

Table 4. Ablation study to prove the effectiveness of image processing steps.

Cases	Segmentation	K-Means Clustering	Accuracy
Case-1	No	No	89.4%
Case-2	Yes	No	92.7%
Case-3	Yes	Yes	97.9%

A higher area under curve (AUC) indicates better overall performance, indicating a higher probability of correctly classifying positive instances compared to negative instances. For our model, leaf smut covered most area under curve and brown spot the least as shown by the ROC curve in Figure 12.

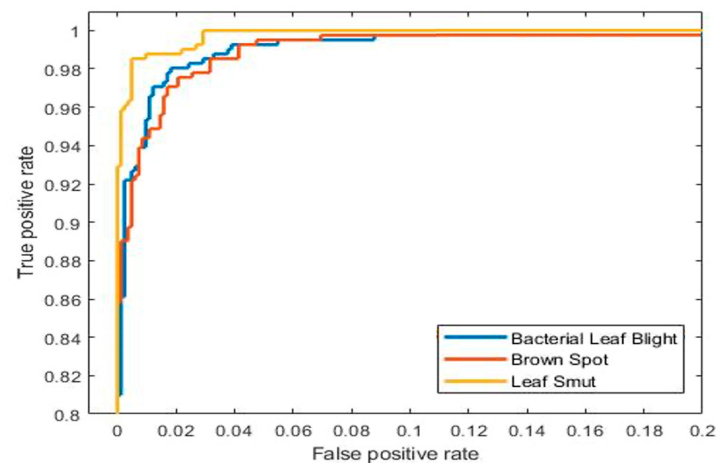


Figure 12. ROC curve for the classification.

A high precision indicates that, when the model makes a positive prediction for a sample, it indicates a higher likelihood of being accurate. A high recall indicates that the model demonstrates a high capability to accurately identify a significant portion of positive samples. It assesses the model's capacity to avoid false negatives. It is clear from Table 5 precision and specificity for brown spot are highest and the recall for leaf smut is highest. For brown spot, the f1 score is also highest and the other two have nearly equal value.

Table 5. Statistical analysis of the trained network performance.

Class	Precision	Specificity	f1 Score	Sensitivity/Recall
Bacterial Leaf Blight	0.9810	0.9904	0.9763	0.9717
Brown Spot	1.0000	1.0000	0.9836	0.9677
Leaf Smut	0.9571	0.9790	0.9781	1.0000

5. Plugging Trained Model into Mobile Application

Mobile apps were developed including the steps of image acquisition, image resizing, image augmentation, removal of background, K-means clustering and CNN model to classify the rice leaf diseases in the agricultural field. To plug the model into the mobile, the model was implemented using the TensorFlow Keras library as shown in Figure 13. The TensorFlow model was converted into a compressed flat buffer with the TensorFlow Lite Converter. The TensorFlow Lite model was placed in the application for classification of the diseases.

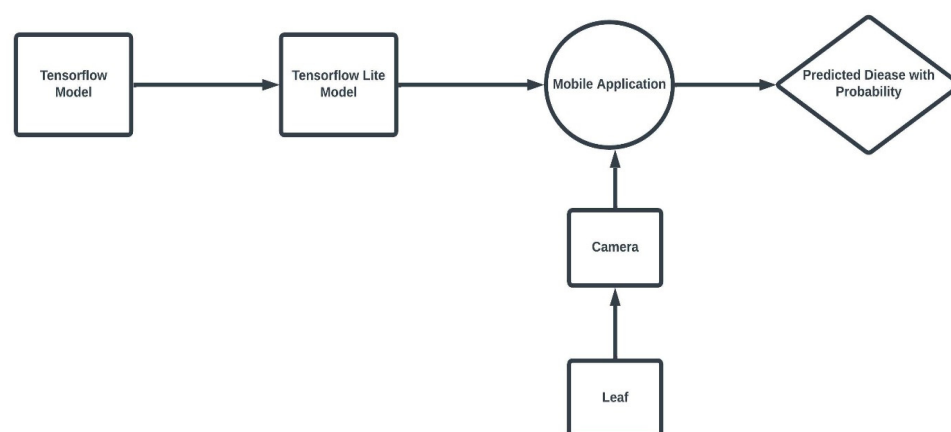


Figure 13. Flow diagram of mobile application development for classification.

The mobile applications were specifically developed to identify and classify rice diseases in agricultural innovations. Figure 14 shows the screenshots which were taken during the classification of rice leaf diseases after selecting pre-captured images from mobile or internet sources.

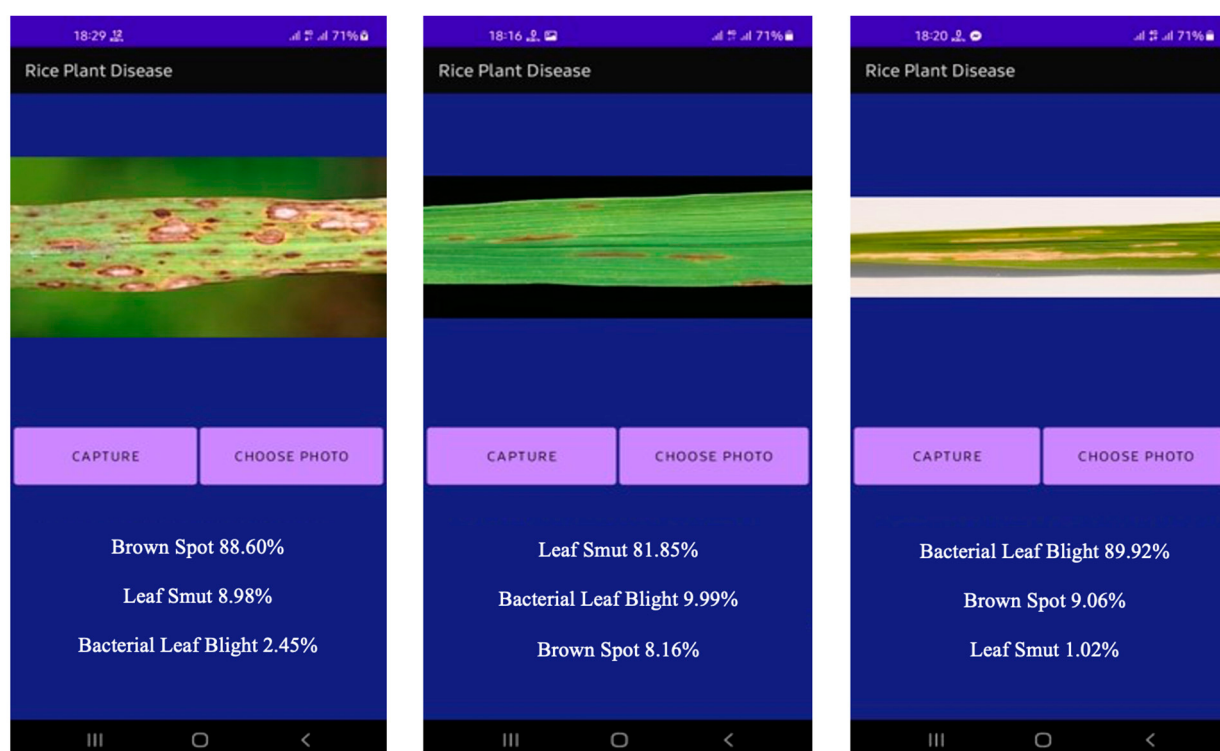


Figure 14. Mobile applications for predicting rice diseases through image processing.

The brown spot-affected image and leaf smut-affected image collected from Internet sources are processed in the mobile app as shown in Figure 14. The mobile app also showed the percentage of possibility of being affected by the disease and classified the diseases with more accuracy through the proposed model.

6. Comparison to Existing Approaches

The researchers used image processing to detect rice diseases so that farmers can easily identify the disease for proper disease management in the agricultural field. The proposed model includes image thresholding and K-means clustering as image pre-processing criteria for getting better performance in disease detection techniques. The model included a CNN

approach to obtain more accuracy in image classification with proper feature extractions. The reliability of the suggested model was compared with other existing models for paddy leaf disease detection or classification as shown in Figure 15.

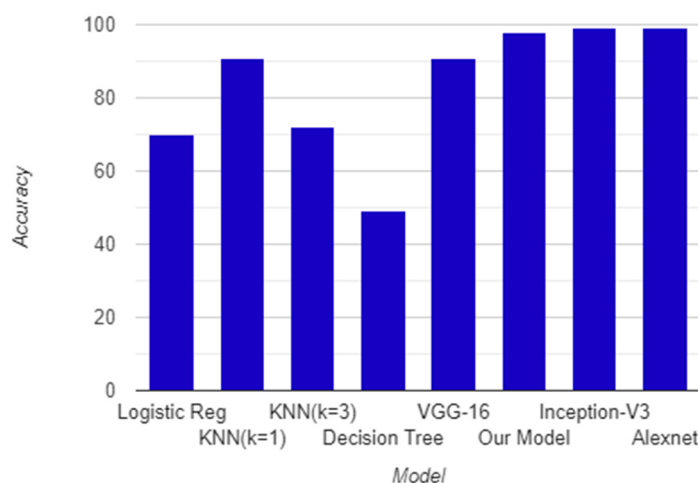


Figure 15. Comparison of accuracies of the proposed model with other existing models.

According to the accuracy diagram in Figure 15, KNN ($k = 1$) shows an accuracy of 90% whereas KNN ($k = 3$) shows an accuracy of 72% in the performance of the disease detection model. The model with VGG-16 criteria obtained an accuracy of 92% for rice disease detections. Though the accuracy obtained by Inception-V3 criteria [9] was higher than the CNN-based model, the transfer learning steps increased the computational complexity of the Inception-V3-based model. In the proposed model, we made a trade-off between network sizes and performance for rice disease detections and classifications. This is because the trained model was faster and more competent for considering small network sizes in mobile applications.

Table 6 shows the reliability of the suggested model compared with the TensorFlow models through Mobile Net, Inception-V3 and AlexNet criteria based on the parameters of processing time and average accuracy in mobile applications. The processing time and accuracy were obtained based on a performance evaluation for 10 affected images in disease detections and classifications. The Mobile Net criteria showed 83% accuracy with a 145 ms processing time while Inception-V3 showed 99% accuracy with 230 ms processing time and AlexNet showed 99.3% accuracy with 195 ms processing time in smartphone applications. Our model showed 97.9% average accuracy but was faster than most other existing models with 103 ms processing time in mobile applications.

Table 6. Average accuracy and time for different models imported in mobile application.

Model	MobileNet	Inception-V3	AlexNet	Our Model
Time	145 ms	230 ms	195 ms	103 ms
Average Accuracy	83%	99.1%	99.3%	97.9%

Only the affected area of the leaf is processed in the proposed model instead of processing the whole leaf which takes significantly less time than entire leaf processing as shown in Table 6. The proposed model for rice leaf disease classification performed well with test accuracy of 97.9% and processing time of 103 ms to use in smart agriculture. IoT-based automated farming also requires this type of model to classify diseases and take necessary steps to manage those diseases efficiently without the necessity of human vision. As rice is the most popular food and the global economy mostly depends on agriculture, the application level of this research is a role-playing concept in the growth and development of agricultural production.

The advantages of the mobile application can also be used to classify diseases at the grass root level. The application can be compatibly used with a properly functioning camera to classify these three popular rice leaf diseases. Thus, paddy leaf disease classification using CNN and image processing technologies with compatibility to use in mobile applications can bring confidence of accurately classifying the diseases in agriculture.

7. Conclusions

This paper presents a new model which is proposed to detect and classify rice disease at its early stages through image processing and a Convolutional Neural Network. The proposed model is able to classify rice disease as bacterial leaf blight, brown spot and leaf smut with a classification accuracy rate of 97.9% and processing time of 103 ms. Integrating several pre-processing steps and the CNN model gives efficiency with reliable outcomes in rice disease detection and classification. The technique is simple enough to be implemented in desktop applications as well as mobile applications with much less computation at feature extractions. Successful implementation of an Android app has been achieved, enabling the identification of diseases in paddy crops and providing relevant solutions. The findings from our experiment reveal that the suggested system possesses the capability of identifying diseases effectively, requiring minimal computational resources. Consequently, users can conserve time and money. The proposed model can be modified for the detection and classification of other agricultural crop diseases which have distinct visual characters. As a future development, the model will also be trained by other regional datasets to acquire more reliability in terms of place, weather and other criteria. Additional features of diseases will be incorporated in the future analysis for establishing a remote sensing system in agricultural innovations.

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