Camera Radial Distance-Based Accuracy of a Bacterial Blight, Brown Spot, and Rice Blast Plant Disease Identification System for Remote Communications Deployment

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Abstract—**Rice plant diseases pose a high threat to rice production. However, the ability to produce better crops is required for any country's economic development. Thus, early detection of rice plant diseases is needed as it can also save the farmer's economic loss. This study presented an identification framework based on AlexNet architecture and transfer learning that can distinguish between healthy leaves, leaves infected with one of the three most common diseases, namely rice blast, brown spot, or bacterial blight, or leaves infected with a disease not covered by any of the three, and displays the results, nature, solutions, and interventions in an application. The Convolutional Neural Network (CNN) and the application were implemented using MATLAB. The datasets used to train the network were obtained from online repositories, and the trained network was tested on actual data taken from the farm. The training-testing division used for labeled images was 80%-20%, and thus the network obtained a validation accuracy of 99.84%. The images taken from the field were captured and proposed to be deployed for remote monitoring via Raspberry Pi connected through Wireless Local Area Network (WLAN) interfaced in a Graphical User Interface (GUI). The identification of the AlexNet achieved a classification accuracy of 94% in testing a 2-inch radial distance of the camera to the subject with images taken from the field. Furthermore, a computed average percentage rating of 80.89% based on the evaluation responses from crop experts and other evaluators proved that the framework was functional, reliable, and efficient.**

Index Terms—**AlexNet, transfer learning, convolutional neural network, rice plant disease, WLAN**

I. Introduction

Agriculture is a significant industry in the Philippines. The country's output meets domestic demand due to its location in Southeast Asia, which has alternating rainy and dry seasons. The Philippines ranked eighth in rice output in 2018, according to the United Nations Food and Agriculture Organization [1]. It is regarded as a critical commodity in the country. However, farmers lose an estimated 37% of the rice crop yearly due to pests and diseases. Pest and disease damage accounts for a significant share of crop losses. A study included an expert-based crop health assessment and numerical estimates of production losses caused by diseases and pests for five main crops globally, including rice [2]. The result of this showed that rice output losses potentially reached 30%. On the other hand, crop management and early and correct diagnosis can significantly reduce losses. Crop protection specialists advise and remind farmers that early diagnosis or identification of rice diseases is the best approach to prevent the potential spread and increase the farmers' losses [3].

Traditionally, diseases were identified based on visual symptoms or pathogen detection in the laboratory. The visual assessment of the disease lesion is a subjective matter. It is susceptible to psychological and cognitive processes that might result in bias, visual illusions, and error [4].

Today's innovative and effective technology can fundamentally transform the agricultural landscape. Most studies believe farmers are now interested in implementing new agricultural practices as agriculture's credence in technology. According to [5], current improvements in data processing technology have helped smart farming expand exponentially, making it a significant ingredient in the success of current agriculture and assisting producers or farmers in the field. In recent decades, there has been a rising idealization with various technologies customized to farmers' circumstances to ensure the goal's long-term viability.

Plant diseases can lower crop yields and provide low-quality agricultural products, damaging the economy and people's livelihoods. As a result, establishing a fast and accurate method for detecting plant diseases is crucial in the agriculture industry. An automated plant disease detection and categorization system was designed and tested in [6], which is a more advanced version of [7]. The improved solution includes six parts and the

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technique used in image processing. They developed a color transformation structure for the RGB leaf images in the first phase and applied device-independent color space transformation. K-means clustering algorithm is used for image segmentation in the second phase. Next is the identification of the pixels that are predominantly green in color. These pixels are masked using particular threshold values derived using Otsu's approach, wherein the primarily green pixels are masked. Then, the pixels with zero red, green, or blue values and pixels on the edges of the infected cluster were eliminated. They calculated the texture features for segmented infected objects in the fifth phase. The retrieved features are sent into a pre-trained neural network during the final phase. This algorithm evaluated five plant diseases: early scorch, cottony mold, ashen mold, late scorch, and slight whiteness. The result of the study established that it can significantly aid in the accurate diagnosis of leaf diseases with minimal computational effort.

In this paper, transfer learning and the pre-trained network AlexNet were used to identify rice plant diseases, specifically rice blast, brown spot, and bacterial blight, which are the three most common rice diseases in the Philippines, according to International Rice Research Institute. The healthy leaves and diseases not covered are included as additional classes. The correct identification of rice plant disease can aid the farmers in applying appropriate treatment to the plant without relying on experts' availability. Furthermore, the experiments show that the camera's ideal distance to the leaf is 2-inch as it shows high accuracy in identifying the disease, which can be used as a reference to identify the disease remotely.

The rest of this paper is organized as follows. Section II presents related works in identifying plant diseases. Section III discusses the methodology, followed by its application in Section IV. The results are presented in Section V and Section VI concludes this work.

II. Related Literature

A. Convolutional Neural Network

A study by Rahman *et al.* [8] utilized the use of CNN architecture, demonstrating a total accuracy of 93.3% in all eight diseases covered. In addition, a presented study using DCNN achieved an accuracy of 95.48% with a total dataset of 500 images. Furthermore, the same dataset was used to train shallow SVM, Back Propagation (BP), and Particle Swarm Optimization (PSO) classifiers which garnered an accuracy of 92%, 91%, and 88%, respectively [9]. Rathore and Prasad also presented a study using CNN architecture in which, in their study, the overall accuracy was 99.61%, with a training-testing division of 80%-20% [10]. In addition, a CNN model was also presented in the study of Hossain *et al.* [11], where an overall accuracy obtained was 97.82% on independent test images. In relation, the use of Multiclass CNN centered on classifying common rice plant anomalies was presented by Atole and Park [12] used 800 total images with 70%-30% training-testing division the accuracy that was obtained was 91.23%. Furthermore, Bari *et al.* [13] proposed a faster R-CNN technique in their study. A total of 2400 images from online and on-field datasets have been collected for the model, which garnered a total accuracy of 99.25%.

B. AlexNet Architecture

Some studies have used pre-trained CNN models to detect plant diseases and showed that Alexnet architecture outperforms VGG-16, Squeezenet, and Inception V3. According to [14], AlexNet has a higher accuracy of 97.4% and takes less time to classify six diseases and a healthy tomato class from a total of 13,262 images compared to the deep VGG-16, which has a classification accuracy of 97.29%. Durmus *et al.* [15] and Setiawan *et al.* [16] used two architecture models, Alexnet and Squezenet, to detect diseases on plants in tomato fields or greenhouses and classify Maize leaf disease, respectively. AlexNet was superior to SqueezeNet for detecting diseases on tomatoes with an accuracy of 95.65% and for Maize leaf disease classification with an accuracy of 97.69%. On the other hand, AlexNet, SqueezeNet, and Inception V3 are three pre-trained CNN models used in a study to identify the severity of tomato late blight disease. The architectures utilized two methodologies: transfer learning and feature extraction. AlexNet outperforms the other two architectures obtaining the highest levels of accuracy in both approaches, 89.69 % and 93.4 %, respectively [17]. In addition, the AlexNet architecture was employed as a classifier in two more studies to detect diseases on grape and mango leaves and plant diseases with datasets, all of which had good accuracy [18], [19]. Lastly, another study utilized an AlexNet neural network to identify three common rice leaf diseases: bacterial blight, brown spot, and leaf smut, and achieved a 99% accuracy [20].

C. Conventional Way of Identification

Traditional methods of identifying rice disease are mainly done manually and tend to be unreliable, expensive, and time-consuming. According to Bari *et al.* [13], the mapping technique for detecting rice diseases is quite simple and straightforward. However, it is easy to make mistakes in identification. Moreover, in the study of Shrivastava *et al.* [21], it was stated that the visual examination of the disease is a subjective matter that may fail to diagnose. In addition, pathogen identification in the laboratory is a time-consuming process. Likewise, according to PhilRice [22], the Conventional assessment methods are not always reliable because symptoms can be caused by various factors, including nutrient or water deficiency.

D. Technology in Rural Areas

According to the National Information and Communications Technology Household Survey, cellular signals cover 92% of surveyed barangays, with 3G technology still dominating rural areas. Some locations still lack telecommunications towers, fiber optic cable, and free WiFi despite having access to electricity. Correspondingly, cellular networks cover around 91% of the barangays, with urban areas having 10% higher coverage than rural towns. Rural areas are more likely to have 3G or 2G as the strongest signal in their localities than urban barangays [23].

According to [23], Filipino families pay an average of PHP 1,280.59 per month for internet connection, with urban households spending more (PHP 1,406.99) than rural households (PHP 1,008.33). By comparing the median monthly family income of poor and low-income families, [24] determined that internet access in the Philippines remains unreasonably expensive.

III. Methodology

This section presents the methodology used in this paper. The training phase, workflow, and validation are discussed.

A. Training Phase

Fig. 1 shows the training process flow chart for the rice plant disease identification system. The first layer of the pre-trained network, an AlexNet convolutional neural network, was fed with a total of 6318 images, comprising 1,370 for each rice plant disease, 897 for healthy leaves, and 1,311 for additional rice plant diseases not covered by the study. These images were classified into folders with the names of the respective rice plant diseases. Loading of photos is the initial stage prior to the training process. The images were categorized into validation and training images. In this system, 80 percent of the images were utilized for training and 20 percent for validation. After loading AlexNet, its final three layers were replaced with a fully connected, a softmax, and a classification layer. With the imageDataAugmenter function, the RGB pictures were resized to 227×227×3 and then used as the network's input. The options for training are then provided. The loss function was reduced using Stochastic Gradient Descent with Momentum (SGDM). Other options, such as the size of the mini-batch, the maximum number of epochs, the initial learning rate, the option for data shuffling, the data to be used for validation during training, the frequency of network validation, an indicator to demonstrate training progress information, and additional options were set to observe the training progress.

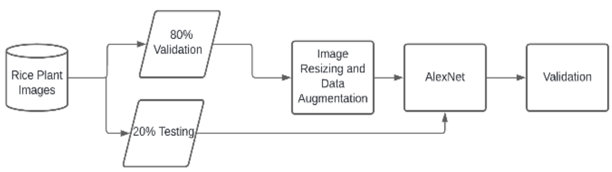


Figure 1. Training and validation process.

B. Data Generation and Acquisition

The researchers obtained images from datasets acquired from Mendeley Data online repositories. The datasets include the most common rice plant diseases, including rice blast, brown spot, and bacterial blight, as well as healthy rice plants and diseases not covered by the study. The datasets comprise a total of 6,318 images covering all the categories. The network was trained on 5055 of these images, while the remaining 1263 were utilized to determine the validation accuracy. In addition, the total accuracy for the whole training period at regular intervals was calculated for each epoch. The overall accuracy score was utilized for performance evaluation. Fig. 2 displays one sample resized image for each rice plant disease exported from the application.

(a) (b) (c)

Figure 2. Exported sample images a.) Rice blast, b.) Brown spot, c.) Bacterial blight.

C. Data Augmentation

The images from the previously stated online data repositories were rotated at 90, 180, and 270 degrees increments. These rotated photos were then added to the total amount of images for each dataset, providing more enhanced resources to enhance the validation accuracy and reliability of the trained model. The size of these images was not modified because AlexNet already has the technique and function that automatically resizes the images to 227×227×3 pixels, which is the required image size for the training phase.

D. Rice Plant Disease Identification

Fig. 3 presents the flow diagram of the rice plant disease identification. The classification of rice disease can detect if the leaf is healthy or infected with one of the diseases recognized by the network. It can also classify if the disease is not covered with no data available.

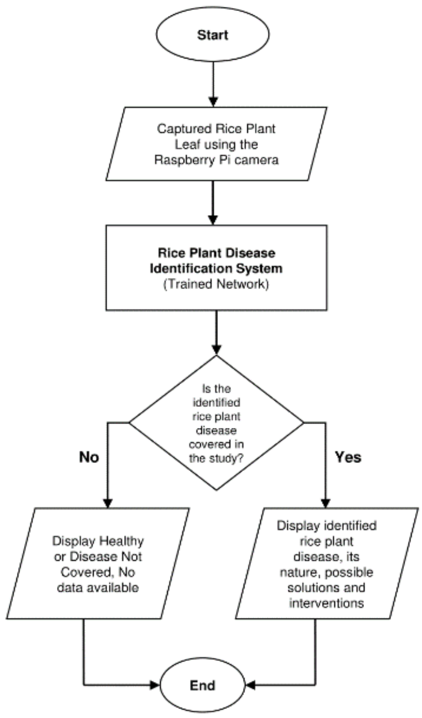


Figure 3. Rice plant disease identification flow diagram.

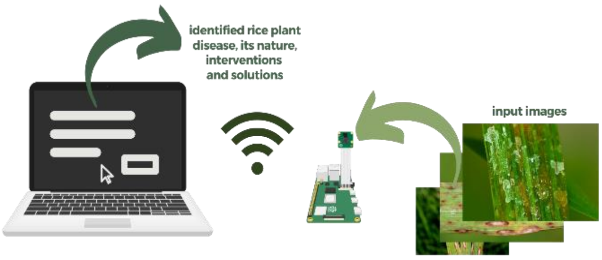


Figure 4. Experimental set-up of the proposed deployment.

Using a Raspberry Pi (RPi) camera or otherwise, an input image for testing was captured. This image was analyzed by the rice plant disease identification system, which used a trained neural network, as illustrated in Fig. 4. Suppose the study covers the discovered rice plant disease. In that case, the application can present the details of the disease, its nature, and the most appropriate solutions and interventions. In contrast, 'Healthy,' 'Disease Not Covered,' or 'No data available' is indicated if the identification is not one of the three rice plant diseases included in the study.

E. *Validation*

The identification framework utilized a confusion matrix to present an output matrix and assess the validation and testing accuracy of the trained model. Classification accuracy was used to evaluate the model's accuracy by calculating the percentage of correct predictions to the total number of samples. After calculating the classification accuracy for each category, the sum of their means is divided by the number of classification categories. Equation (1) shows the equation for the classification accuracy per category.

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Samples}} \tag{1}$$

Equation (2) presents the mathematical representation of the Jaccard Similarity Index, which was employed in the study to evaluate further and cross-validate the accuracy of the network with the ground truth. The Jaccard index ranges from 0 to 1. It determines which elements from the two categorical data sets are shared or unique. The set of ground truth is represented by A, and B represents the tested category of the disease, and $|\cdot|$ the cardinality of the set.

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|} \tag{2}$$

IV. Application

The Waterfall Model presented in Fig. 5 was utilized in developing the application to discuss the procedures for its completion comprehensively. It is a structural model that adopts a linear and sequential method in system development presented.

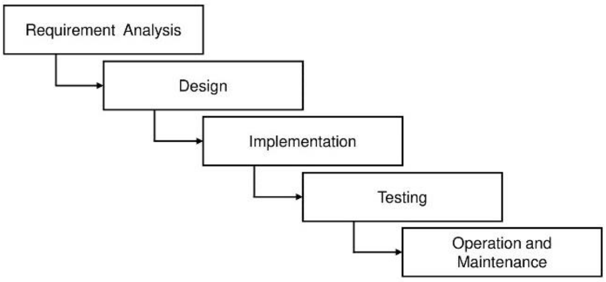


Figure 5. Waterfall model for the application.

A. *Requirement Analysis*

In developing the application, initial requirements must be determined. The researchers collected rice plant leaves images that involve the five categories from Kaggle and Mendeley Data. Also, the nature of the diseases and the solutions and interventions for each to be presented on the application were gathered. The collected images were used to train a convolutional neural network using AlexNet architecture. The RPi camera was connected to the RPi microcontroller to transmit the image to the application created and designed using the MATLAB App Designer. Fig. 6 shows the interface developed with the example leaf identified.

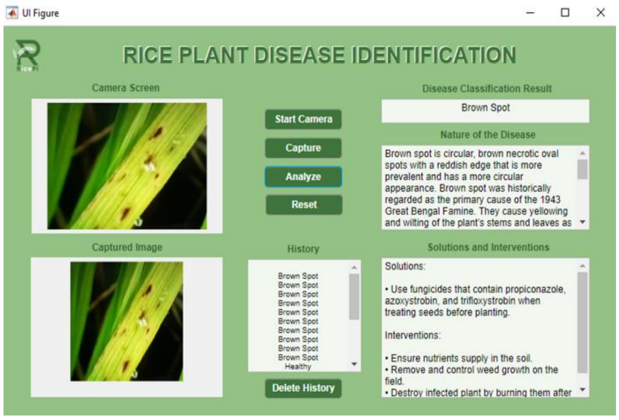


Figure 6. User interface of the identification process.

B. *Implementation*

The functions for the AlexNet architecture are imported through the Deep Learning Toolbox Model for the AlexNet Network of MATLAB. Additionally, the MATLAB Support Package for RPi Hardware must be installed in the software to connect the RPi microcontroller and camera to the application. MATLAB App Designer was the main platform to develop the necessary application for the study. The researchers used an Acer Nitro 5 personal computer with specifications of 8 GB RAM and Intel(R) Core(TM) i510300H CPU @ 2.50GHz processor. The application's functionality and features were based on the necessary information enumerated on the specific objectives. The experimental configurations that were used are summarized in Table I.

TABLE I. PARAMETERS USED IN TRAINING

Deep Learning Architecture	AlexNet
Training Mechanism	Transfer Learning
Dataset Type	Colored Images with Background
Data Division (Training-Testing)	80%-20%
Number of Epochs	6
Solver Type	SGDM
Base Learning Rate	0.0001

C. Testing

The testing procedure for the application includes unit testing, system testing, and acceptance testing. The unit testing was conducted to assess the small-scale demonstrable features of the application individually. The test case was also performed for the system testing to determine if the different features perform as expected and confirm if it complies with all necessary standards, guidelines, and specifications. After undergoing the unit and system testing, the researchers let the crop experts and other research respondents use the application and answer the evaluation form reformed from ISO 25010 for the acceptance testing.

D. Operation and Maintenance

After conducting effective testing procedures, the researchers included the features recommended by the test correspondents using the app designer. The improved application was packaged through the software and transferred to the user's personal computer. Subsequently, to completely deploy the application, the researchers assigned an IP address for the RPi microcontroller through the installed MATLAB support package for RPi Hardware to connect it to the user's WLAN.

V. RESULTS AND DISCUSSION

Fig. 7 shows the visualization of the network architecture and detailed information about the network layers of the trained network. The pre-trained AlexNet's last three layers are set up for 1000 classes. For the new identification problem, these three layers are replaced by the class of rice plant diseases. For achieving the objective of this study, these layers were replaced by a fully connected layer, a softmax layer, and a classification layer.

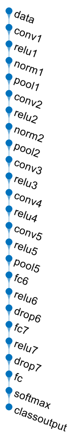


Figure 7. Layers of the trained network.

Fig. 8 shows the training progress, validation accuracy, and training time. The network was trained using 5055 images containing the three most common rice plant diseases, healthy, and the diseases not covered by the study. The other 1263 images were used to determine the validation accuracy of the trained network. Upon training, the computed validation accuracy was 99.84%, indicating that 1261 images were correctly identified and two were wrong. The total elapsed training time utilizing 6318 images was 167 minutes and 35 seconds.

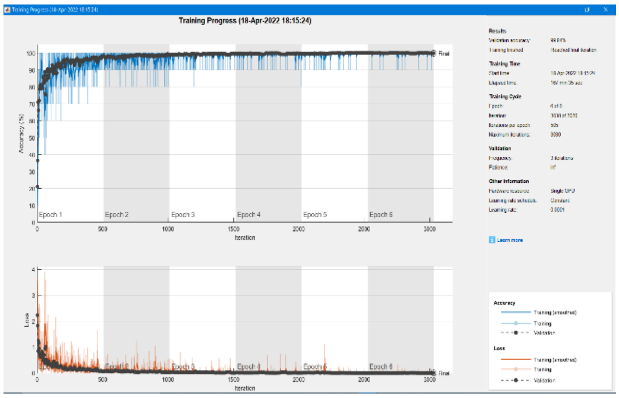


Figure 8. Training progress of the trained network.

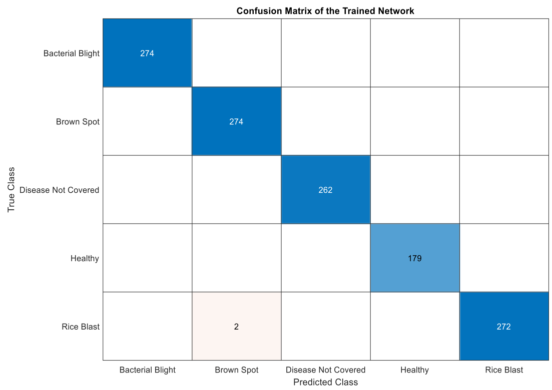
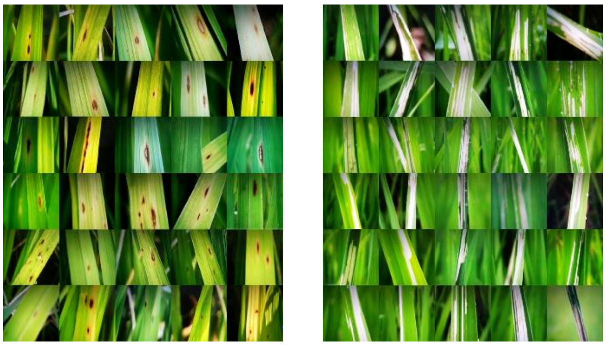


Figure 9. Confusion matrix for the trained network.

Based on the confusion chart in Fig. 9, two images were identified incorrectly out of the 1263 images used for testing. The true class of these incorrect predictions is rice blast, but they were identified as brown spots. To calculate the validation accuracy using the classification accuracy formula, we need to get the ratio of the correct predictions to the total number per row and get the overall mean. With the use of (1) and (2), the computed overall classification accuracy was 99.85%.

The network showed good accuracy and was tested on a rice farm in Brgy. Panipuan, Mexico, Pampanga, Philippines. Due to the limited presence of rice diseases in the field, only the brown spot and bacterial blight were tested, along with the healthy leaves, which the crop expert verifies. The captured images were set to 2-inch and 4-inch radial distances to test the accuracy in identifying the disease to the camera's distance to the object. Fig. 10 shows the captured data from the field of a.) brown spot and b.) bacterial blight



a.) Brown spot b.) Bacterial blight

Figure 10. 2-inch radial distance captured images.

The summary of the accuracy of the camera's distance to the leaf gathered from the testing procedure is presented in Fig. 11. A total of 150 images were tested, 30 from each category: bacterial blight, brown spot, disease not covered, healthy, and rice blast. The images were also captured using 2 and 4 inches as radial distances, the leaves were analyzed, and the diseases were identified using the trained neural network.

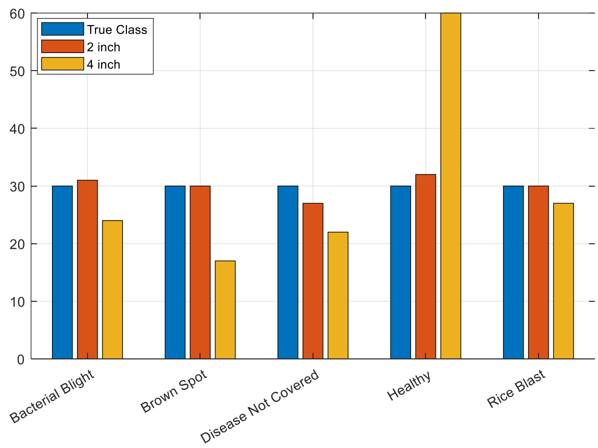


Figure 11. Summary of actual identification results.

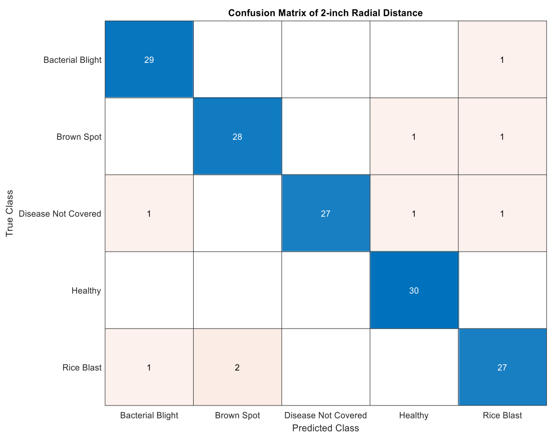


Figure 12. Confusion matrix for the 2-inch radial distance testing.

In Fig. 12, the confusion matrix is obtained by comparing the ground truth as a reference and the images captured with a radial distance of 2 inches. From the confusion matrix, the trained network has mistakenly identified one bacterial blight as rice blast, two brown spots as healthy and rice blast, three diseases not covered as bacterial blight, healthy and rice blast, and three rice blast as bacterial blight and brown spot. The network identified the 30 images tested for healthy leaves correctly. Generally, 141 images were accurately identified by the network.

Fig. 13 shows the confusion matrix obtained by comparing the ground truth as a reference and the images captured with a radial distance of 4 inches. The trained network has mistakenly identified 18 bacterial blights as mostly healthy and rice blast, 15 brown spots as mostly healthy and rice blast, eight diseases not covered as bacterial blight, healthy, and rice blast, and 11 rice blast as bacterial blight and brown spot. The network identified the 30 images tested for healthy leaves correctly. Generally, 98 images were accurately identified by the network.

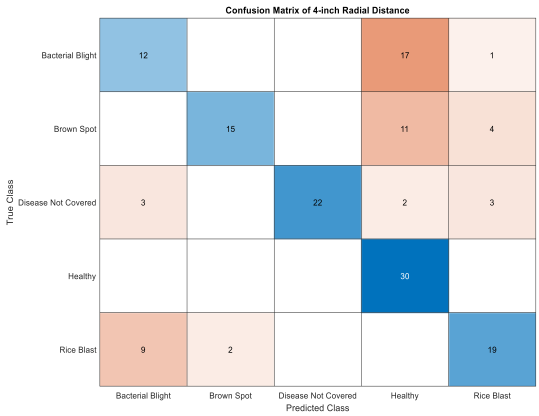


Figure 13. Confusion matrix for the 4-inchesradial distance testing.

Table II summarizes the classification accuracy and Jaccard index for each category upon testing. The highest obtained accuracy for the 2 inches radial distance was from the healthy leaves with 100%, while the lowest was from both the disease not covered and rice blast with 90% accuracy. Additionally, bacterial blight and brown spot classification accuracies were 96.67% and 93.33%, respectively. Cross-validation of the categorical data achieves the highest Jaccard index of 0.9355 obtained from the healthy leaves. In contrast, the lowest index of 0.8182 was from the rice blast-infected leaves. Furthermore, the Jaccard index of bacterial blight, disease not covered, and brown spot correspondingly were 0.9063, 0.9000, and 0.8750.

Additionally, the highest obtained accuracy for the 4 inches radial distance was from the healthy leaves with 100%, while the lowest was from the bacterial blight with 40% accuracy. Cross-validating, the highest Jaccard index of 0.7333 was obtained from the disease not covered. In contrast, the lowest index of 0.2857 was from the bacterial blight infected leaves. The Jaccard indices indicate the network's performance in overall identifying the rice plant's status and correctly identifying and misclassifying the network. The misclassification affects the Jaccard index, showing that the 4-inch radial distance performs poorly.

TABLE II. SUMMARY OF CLASSIFICATION ACCURACY AND JACCARD INDEX FOR EACH CATEGORY

Category	**Classification Accuracy (%)**		**Jaccard Index**	
	2 Inches	4 Inches	2 Inches	4 Inches
Bacterial Blight	96.67	40	0.9063	0.2857
Brown Spot	93.33	50	0.875	0.4688
Disease Not Covered	90	73.33	0.9	0.7333
Healthy	100	100	0.9355	0.4915
Rice Blast	90	63.33	0.8182	0.5
Average	94	65.33	0.887	0.4952

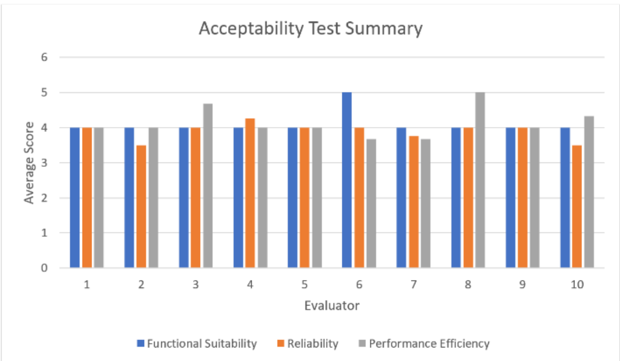


Figure 14, Summary of acceptability testing.

In Fig. 14, the summary of the acceptability test to determine the functional suitability, reliability, and performance efficiency of the application is illustrated. The computed average scores for each of the evaluated parameters of the application were 4.1, 3.9, and 4.13, respectively, which are also equivalent to 82%, 78%, and 82.37%, respectively, correspondingly. The computed overall average percentage of the application accumulated from the percentage score per parameter was 80.89%, and their average percentages showed that the evaluators agreed that all items were satisfied by the system.

VI. CONCLUSION AND RECOMMENDATION

Utilizing a pre-trained AlexNet that was trained using transfer learning with images with background achieves a validation accuracy of 99.84%. The trained network could classify bacterial blight, brown spot, rice blast, and the diseases not covered. Additionally, healthy leaves are added to the classes for identification. The system deployment proposed using an RPi to capture the images remotely, interfaced with a GUI connected using WLAN. After conducting multiple tests on two different radial distances, an inference may also be drawn that the 2 inches radial distance is more reliable with 94% accuracy than the 65.33% accuracy of 4 inches distance. The average time delay of 21.7163 seconds in executing ten identification processes also implies that the time efficiency of the framework is economical. In addition, based on the computed overall average percentage rating of 80.89% from the responses of the crop experts and other evaluators. For further improvement, more images can be utilized from various field settings in training the convolutional neural network. The number of categories can also be increased to expand the rice plant disease identification scope. For better portability, the trained network, RPi camera, and application to the RPi microcontroller can also be integrated.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

C. J. Canlas, C. M. Cortez, R. A. D. Cruz, J. R. Padua, A. G. Timbol, and J. Yumul worked on developing the neural network and interface, validation, formal analysis, investigation, data collection, and draft writing. E. Trinidad made the review, editing, and draft writing and served as the adviser. L. Materum made the funding acquisition, methodology consultant, review, editing, and co-advising.

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