The Use of Convolutional Neural Networks and Visual Attention to Determine Infected Rice Plants

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ABSTRACT
Detecting disease-infected rice plants is essential in maximizing the crop yield being produced by local farmers. This becomes a challenge as the most prominent method in plant disease detection is through manual, visual assessment. In this study, the proponents developed a machine learning approach in detecting infected rice plants with the following diseases: (1) Brown spots; (2) Hispa; (3) Leaf or Rice Blasts. The proponents used a Convolutional Neural Network, using the AlexNet architecture, with the intention of improving its results with the use of visual attention. The results indicated that the Convolutional Neural Network without visual attention is the best in terms of mean accuracy which yielded 91.90%, while the Convolutional Neural Network with visual attention yielded 91.67%. However, in the best case scenario the standard deviation of Convolutional Neural Network with Visual Attention has an accuracy rate of 93.69%. The analysis indicates that CNN without attention is the most versatile model to use in classification.

CS Concepts
Computing Methodologies ➝ Artificial Intelligence ➝ Computer Vision → Plant Disease Recognition → Convolutional Neural Network

Keywords
Rice Leaf Disease; Disease Detection; Convolutional Neural Networks (CNN); Visual Attention; Rice Disease; Plant Disease Recognition

1. INTRODUCTION
Technological improvements allow society to supply sufficient resources to be able to fulfill the needs of our population growth. This paper is regarding an approach to determine infected rice plants by the use of convolutional neural networks and visual attention. Thorough diagnosis of plant diseases is one of the fundamentals of precision agriculture. Eliminating excessive consumption of other resources is important for establishing sustainable production. A thorough study intended at identifying plant infections based on the plant's look and visual symptoms might be immensely beneficial to the farming industry. Advancements in computer vision provide the ability to broaden and strengthen the practice of accurate plant protection, while also expanding the market for computer vision technologies in precision agriculture.

2. BACKGROUND OF THE STUDY
The Philippines, with a population of over 100 Million, is the world's sixth-largest consumer of rice [24]. Rice is an essential staple in the country, served at almost every meal of the day. Alongside the supply is the demand and as the population swells, the country's supply of rice begins to be disproportionate [24]. With more farms being converted into factories and housing developments, less homegrown rice yield is to be anticipated, making rice importation a necessity [24].

As the demand for rice is disproportionate, maximizing the yield of rice is a significant task. According to the International Rice Research Institute [27], rice plant disease infection causes a declination of crop yield. Additionally, it has been found that around 24% to 41% of rice crop yield can be lost due to diseases. Instances of rice plant diseases include brown spot, hispa, and rice blast. Detecting rice plant diseases is important in order to maximize the yield produced by the local farmers.

The most prominent method in plant disease detection is through manual, visual assessment. This method is exhaustive and requires the assessor knowledge on the different diseases the rice plant may have. A way in reducing these manual tasks is through the process of automation. Machine learning provides an avenue for farmers to make better decisions, as it provides information regarding the crops and environment [16].

A study by Lu et al. [14] enumerates the three main stages in using machine learning methods to plant disease detection. First, removing the background or segmenting the infected part found in the image by various preprocessing techniques. Second, extraction of distinct features for further analysis. Lastly, predicting the class to categorize the features using supervised or unsupervised learning algorithms. The features used in classifying plant diseases are the texture, type, and color of plant leaf images. Examples of plant disease classification models are support vector machines, K-nearest neighbors, and random forests [20]. However, most traditional machine learning algorithms are not suitable for real-time classification because of their relatively poor performance. Also, these methods extract features by hand, and it needs to be designed manually, which can be exhausting and time-consuming [20].

A machine learning approach in detecting features from a region of interest is essential to detecting rice plant diseases. In particular, the use of Convolutional Neural Networks could be employed, as it is widely used for image recognition and analysis [30]. A study conducted by Jadhav (2019), used convolutional neural networks in identifying three soybean diseases out of soybean leaves. They used a pre-trained CNN as the feature extractor and classifier [46].

To enhance the capability of CNNs in detecting features, a study conducted by Fernandez [7] used an end-to-end neural network with an attention model to recognize facial expressions. The study coupled an attention module to create an attention map for relevant facial features, which will then be fed to a ResNet34 deep convolutional neural network for classification. Results showed that the attention module improves the recognition of facial expressions.

The goal of this study is to create a convolutional neural network model, with visual attention in order to determine rice plants infected with the following diseases (1) Brown spots; (2) Leaf Smut; (3) Bacterial Leaf Blight.

3. REVIEW OF RELATED LITERATURE

3.1 Disease Detection

The use of modern technology gave human society the means to feed 7.9 billion people in the world [41]. However, food security remains a threat as several factors endanger food sources which include the following: climate change, the decline in pollinators, plant diseases, etc. Among the stated threats, the one that is currently affecting the most in terms of crop yield is the plant diseases where the global economy loses 220 billion USD and 20 to 40 percent of global crop production annually [17].

Many efforts have been made to control plant disease, identifying the disease is the first step in efficient disease management. Historically, there were many attempts made to counteract plant diseases. Agricultural organizations or other institutions were built and have local plant clinics. Online website applications were programmed for people, especially farmers, to remotely ask for an expert's opinion. Mobile phones were groundbreaking as 69% of the entire population in the world has access to mobile broadband allowing the people to take a picture of the plant and send an image to an expert to efficiently ask for a diagnosis [17].

Identifying the rice plant disease is imperative as it helps reduce the economic loss and ascertain food security to feed more people. The traditional method of disease detection used by farmers and experts was manually examining each crop and this method can be time-consuming and costly. It proves to be infeasible for millions of small and medium-sized farms in the entire world. To resolve this problem, the Computer Scientist has taken this into account and built models through Deep Learning that will be used to automatically identify what type of plant disease is present within the plant, particularly the rice.

3.1.1 Deep Learning

Deep learning refers to the use of an artificial neural network architecture that contains a large number of processing layers as opposed to the "swallower" architecture of traditional neural networks methodologies [6]. When deep learning architectures started to evolve, researchers began to apply them to image recognition and classification, and these architectures have also been implemented for different agricultural applications [26]. For example, it was used for the classification of leaves in challenging conditions performed by using an author-modified Convolutional Neural Network and Random Forest classifier to achieve a classification accuracy of 97.3% [26].

3.1.2 Computer Vision

Computer Vision is a subset of deep learning [23]. It trains computers and systems to extract information from digital images, videos, and other visual outputs [11]. There are numerous applications of Computer Vision such as the following: robotics, autonomous vehicles, healthcare, manufacturing, and agriculture. The methodologies used by Computer Vision are done through image classification, object detection, object tracking, facial recognition, and pattern detection [26]. The one that will be focused on in this study will be agriculture, which will be using computer vision through image classification to identify plant diseases [28]. In a study conducted by Voulodimos et al. [39], the researchers evaluated and compared three models used in computer vision, namely the Convolutional Neural Network (CNN), Deep Belief Networks (DBNs), and Deep Boltzmann Machines (DBMs), and Stacked (Denoising) Autoencoders. The researchers stated that CNN is generally better especially in cases wherein the input is visual-oriented and emphasized the two strengths of CNN. First is its feature learning and second is it's invariant to transformations such as rotation and scale.

3.2 Common Rice Diseases

3.2.1 Brown Spots

Brown spots are one of the most distinctive and most damaging diseases of rice in the world. Caused by *Bipolaris oryzae*, it is linked to many important epidemics in the world. The characteristics of brown spots in leaves have shown to include light-reddish brown lesions with a gray center surrounded by a dark to reddish brown margin, and then a bright yellow halo. It spreads from plant to plant by airborne spores. Additionally, Brown spots result in a reduction of yield during the plant's reproductive stage as evidently reported during an epidemic during 1942 where the reported field losses vary broadly from 6 to 90% [2].

Another type of the brown spot disease is called the narrow brown leaf spot. It is an economically significant type of fungal disease caused by *Cercospora janseana*. Due to its sporadic occurrence and varied effects from year to year, this disease has only been considered minor. The pathogens of this disease mainly attack the leaves, sheaths, internodes, panicle branches, and glumes of the plant. The narrow brown leaf spots are long, narrow, and cinnamon-brown in color. The effects of this disease can cause premature ripening and leaf death, thus reducing overall yields. The pathogen of this disease is seedborne, thus disseminating it from seed to seed [37].

3.2.2 *Leaf smut*

Leaf smut is a disease caused by the fungus *Entyloma oryzae*. It produces slightly elevated, angular, black spots on both sides of the rice leaves [9]. Additionally, the characteristic patterns of Leaf smut are small black linear lesions on leaf blades, and leaf tips which turn gray and dry [1]. Heavily infected plants result in leaves turning yellow and leaf tips turning gray. The disease often occurs late in the growing season and is favored by high nitrogen rates [9].

A study was conducted where biological agents in the form of soil based antagonist fungi is used to prevent the spread of *Entyloma oryzae* pathogen. 10 types of antagonist fungi were used as comparison to the growth of *Entyloma oryzae* pathogen on multiple experiments. The results for this study shows that *Trichoderma viride, Gliocladium virens and Trichoderma harzianum* are the most effective biological agents in suppressing the growth of Entyloma oryzae pathogen in crops [18].

3.2.3 *Bacterial leaf blight*

The bacteria *Xanthomonas oryzae pv. oryzae* is the causal agent of Bacterial leaf blight (BLB) and a typical vascular pathogen. Investigations show that the bacterial masses of this pathogen are abundant in the lumen of xylem vessels, whereas it is not present in other vascular elements. Additionally, the inner location of spiral and ring vessels in the area where the bacterium is abundant was digested. This finding suggests that the bacteria *Xanthomonas oryzae pv. oryzae* obtains nourishments such as pectic substance from the lumen of xylem vessels for its multiplication [21].

BLB is also one of the destructive rice diseases that causes substantial loss in both rice quality and quantity [10], as well as in rice production [16].

3.3 Convolutional Neural Network

Traditional disease detection methods rely on extracting handcrafted features from the acquired images to identify the type of infection. Also, the performance of these works solely depends on the nature of the handcrafted features selected. This can be addressed by learning the features automatically with the help of CNN [43].

Convolutional Neural Network (CNN) is a form of Artificial Neural Network (ANN) architecture that is primarily used to solve image-driven pattern recognition tasks [44]. CNN contains layers of artificial neurons which imitates the behavior of neurons in the brain. CNNs have demonstrated remarkable performance in various computer vision tasks. In image classification tasks, particularly in identifying crop diseases, CNNs outperform traditional image processing algorithms.

Studies comparing the performance of CNN against other methods for detection of crop diseases have shown that CNNs yield the best result as compared to other methods, with an accuracy difference ranging from 3% to 28.89% [5]. Another study conducted on the Plant Village Dataset consisting of three (3) diseases in tomato plants using two (2) different deep architectures namely, (a) CNN with residual learning and (b) CNN with attention mechanism produced an 95% and 98% accuracy in identifying the diseases, respectively [43]. A study by Hassan et al. (2021) replaced the standard convolution with depth-separable convolution. Wherein, the replacement reduced the number of parameters and computational cost for model implementations [45]. The authors implemented different CNN architectures such as InceptionV3, InceptionResNetV2, MobileNetV2, and EfficientNetB0 for their models to classify the open dataset containing 14 plant species and 36 different categorical disease and healthy classes in which they produced accuracies of 98.42%, 99.11%, 97.02%, and 99.56% respectively. The authors evaluated the performance of the implemented models with different parameters such as batch size, dropout layers, and the number of epochs. They concluded that deep CNN models are promising and can greatly improve the identification of diseases in agricultural systems [45].

With the following results produced by previously made models for plant disease detection, the proponents would be using a CNN model for classifying diseases found in the Rice Diseases Dataset made by Marsh (2020) [48].

3.4 Visual Attention

Visual attention, in a neuroscience context, refers to cognitive processes that allow us to selectively process vast amounts of information through prioritizing only certain aspects of the visual field, ignoring irrelevant information [13].

Inspired by the aforementioned mechanism, researchers in the field of computer vision tried to find the model of visual selective attention to simulate the visual perception process of humans in observing images [42]. There are six categories of attention in computer vision, which are: Channel attention, which generates attention masks across a channel domain for selecting important channels; Spatial attention, which generates attention masks across spatial domains to select important spatial regions or predict the most relevant spatial position directly; Temporal attention, which generates attention masks in time to select key frames; Branch attention, which generates attention masks across different branches to select significant branches; Channel & spatial attention, which generates a joint 3-D channel, height, width attention mask to be used in selecting important features; Spatial and temporal attention, which produces joint spatio-temporal attention masks to focus on informative regions [47].

4. METHODOLOGY

This section discusses the methodology employed in the study. Firstly, the researchers acquired the Rice Leaf Diseases Dataset from Kaggle. Afterwards, the images are then subjected to preprocessing methods such as image resizing, filtering, thresholding, coloring, histogram equalization, and splitting and merging. The images are then shuffled and divided as training and test sets.

The Convolutional Neural Network (CNN) using AlexNet architecture was implemented alongside the Visual Attention Model. After classifying the testing dataset, the model was then evaluated through its validation and training Accuracy, as well as its Error, Precision, Recall, and F1-score. K-Fold Cross Validation was also utilized to validate the accuracy scores.

4.1 Preprocessing

In this section, the preprocessing methods will be discussed. The extracted dataset containing 2,520 images was classified into three categories based on the labels found in the dataset, namely Bacterial leaf blight (BLB), Brown spot, and Leaf smut. The methods found in the OpenCV library were primarily used in the data preprocessing.

After classification, the images were resized into 224x224 dimensions to generate the input shape. To ensure the model focuses on the essential parts in the image, particularly the rice plant, image thresholding was employed. It is a type of image segmentation wherein the pixels in an image are changed to make the image easier to analyze. A filter was generated through the grayscale colormap of the image. The filter was then placed on the actual image to generate the segmented image.

Furthermore, to improve the visibility level of the images, the CLAHE enhancement method was employed. Contrast Limited Adaptive Histogram Equalization (CLAHE) is a variant of Adaptive Histogram Equalization (AHE), and serves the purpose of improving the contrast in an image. The segmented images were then merged with the CLAHE filter. Additionally, a 2D filtering function with a kernel was also implemented alongside Gaussian filtering before proceeding to the implementation of the model.

4.2 Convolutional Neural Network

In this section of the methodology, it will briefly discuss the Convolutional Neural Network (CNN) architecture that was used for recognizing and classifying the type of disease a rice leaf is infected with, particularly it will be recognizing if the rice is infected with brown spots, hispa, or leaf blasts.

A CNN model was implemented to recognize rice leaf diseases. To implement the model, methods from the TensorFlow library were used, such as Keras. The model was also trained, using the training dataset containing 2520 images, to find distinct features in the images, which are used to distinguish and classify the rice leaf diseases, as either having bacterial leaf blight, brown spots, or leaf smut. After training the model, it was tested using the testing dataset to evaluate the performance of the recognition system.

Specifically, two CNN models were created, both of which utilized the AlexNet architecture. The first model was implemented without Visual Attention, whilst the second model was with Visual Attention. The first model was built with several layers consisting of an input layer, 5 convolutional layers, 5 batch normalization layers, 3 max pooling layers, a flatten layer, 3 dense layers, and 2 dropout layers. The specific parameters of the proposed model are shown in Table 4.1., which consist of the layer, number of filters, filter size, stride, feature map, and the activation function utilized.

Table 4.1. AlexNet Architecture of the Proposed Model

Layer	# Filters	Filter size	Stride	Feature map	Activ. func.
Input	-	-	-	224x224x3	-
Conv1	96	11x11	4	56x56x96	ReLu
MaxPool1	-	3x3	2	27x27x96	-
Conv2	256	5x5	1	27x27x256	ReLu
MaxPool2	-	3x3	2	13x13x256	-
Conv3	384	3x3	1	13x13x384	ReLu
Conv4	384	3x3	1	13x13x384	ReLu
Conv5	256	3x3	1	13x13x256	ReLu
MaxPool3	-	3x3	2	6x6x256	-
Flatten1	-	-	-	9216	-
Dense1	-	-	-	100	ReLu
Dropout1	rate=0.5	-	-	100	-
Dense2	-	-	-	100	ReLu
Dropout2	rate=0.5	-	-	-	-
Dense3	-	-	-	3	Softmax

Additionally, the proposed model was implemented with the following parameters, particularly a batch size of 32, a validation split of 1/9 or 0.11, and a number of epochs set to 50. The specific parameter values yielded excellent performance in its metrics, to be shown in the results section of the study.

4.3 Visual Attention

For this section, the Visual Attention will be briefly discussed. In the implementation of the second proposed model, which is the Convolutional Neural Network with Visual Attention, the methods found in TensorFlow library were also used. The source code of the model was also acquired from a public repository in GitHub [15]. Among the six categories of attention in computer vision, the proposed model utilizes the Channel and Spatial Attention.

Similar to the first model, a CNN model with AlexNet architecture was implemented to recognize rice leaf diseases, namely bacterial leaf blight, brown spots, and leaf blast. Thus, the previous layers of the first model were retained, with the addition of 10 layers, each convolutional layer having a channel attention and spatial attention layer. The specific parameters of the Attention layers are shown in Table 4.2. After the training and testing of the model with Visual Attention, its performance will also be evaluated and compared with the first model.

Table 4.2. Visual Attention Layers of the Second Model

Layer	Feature map	Activ. func.
ChannelAttention1	56x56x96	ReLu & Sigmoid
SpatialAttention1	56x56x96	Sigmoid
ChannelAttention2	27x27x256	ReLu & Sigmoid
SpatialAttention2	27x27x256	Sigmoid
ChannelAttention3	13x13x384	ReLu & Sigmoid
SpatialAttention3	13x13x384	Sigmoid
ChannelAttention4	13x13x384	ReLu & Sigmoid
SpatialAttention4	13x13x384	Sigmoid
ChannelAttention5	13x13x256	ReLu & Sigmoid
SpatialAttention5	13x13x256	Sigmoid

5. EVALUATION

The evaluation of the model will be using statistical metrics that determine whether the proposed model of CNN with visual attention is good or not. Good accuracy in machine learning is subjective where the baseline starts from 70% which is stated to be a great model performance [3]. The statistical metrics that will be used to evaluate are the following: Accuracy, Error, Precision, Recall, and F1-Score.

5.1 Dataset

The dataset is taken from Kaggle which is a reputable source of datasets. The information available within the said platform is used primarily for machine learning, data science, and analytics. Rice Diseases Dataset made by Marsh (2020) will be used to train, evaluate, and test the CNN model with Visual Attention that is labeled with its corresponding classification of rice disease. There are 40 images per classification that underwent data augmentation which yields 2,520 images [48].

5.2 Statistical Metrics

Accuracy measures the difference between the predicted label and the actual label where the higher it is then the model will yield a better prediction. The formula for accuracy is shown in (5.1).

$$Accuracy = \frac{\#\ of\ correct\ predictions}{\#\ test\ instances} \quad (5.1)$$

The discussion of the confusion matrix is required as it will serve to help understand the formula for precision and recall. A sample binary confusion matrix will be showcased in Figure 5.1 wherein there are four possible values which are true positive, false positive, false negative, and true negative. True positive means that the actual label and predicted label are true, false x`positive means that the actual label means the actual label is false and predicted label is true, false negative means that the actual label is true and predicted label is false, and as for true negative both actual and predicted label is false.

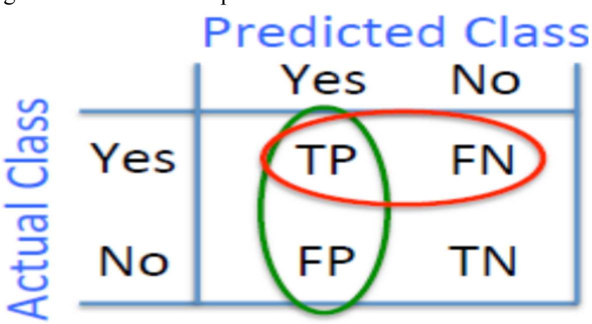

Figure 5.1 Confusion Matrix (Fidler, S., 2015)

Precision is the statistical metric that measures the probability to determine the correct and predicted to be correct by the model. The formula for precision is shown in (5.2).

$$Precision = \frac{TP}{TP + FP} = \frac{\#\ of\ correct\ predictions}{\#\ of\ all\ recognized\ words} \quad (5.2)$$

Recall is the metric that determines how well the model is able to classify relevant data. It is similar to precision but the main difference is focusing with the actual label rather than the predicted to be correct by the model. The formula is shown in (5.3).

$$Recall = \frac{TP}{TP + FN} = \frac{\#\ of\ correct\ predictions}{\#\ of\ all\ expected\ words} \quad (5.3)$$

F1-score is the harmonic combination of precision and recall. A higher value in the F1-score indicates that the model has a high predictive power. The formula is shown in (5.4).

$$F1 - score = 2 * \frac{precision*recall}{precision+recall} \quad (5.4)$$

6. DISCUSSION OF RESULTS

Convolutional Neural Network with Visual Attention is the model created for the purpose of classifying an image with its actual label. The model yielded an accuracy rate of 91.67% in training, 86.51% in validation, and 87.69% in testing. According to Barkved (2022), an accuracy above 70% are models that performed greatly therefore it is a model that is made by the proponents that is ideal for classifying rice plant diseases.

Confusion Matrix allows the proponents to visualize the predictions made by the model. It establishes the relationship of the actual and predicted labels by determining how much are true positive, true negative, false positive, and false negative. As seen in Figure 6.1 the dark colors forming a diagonal line represents how many true positives that have been predicted correctly by the model.

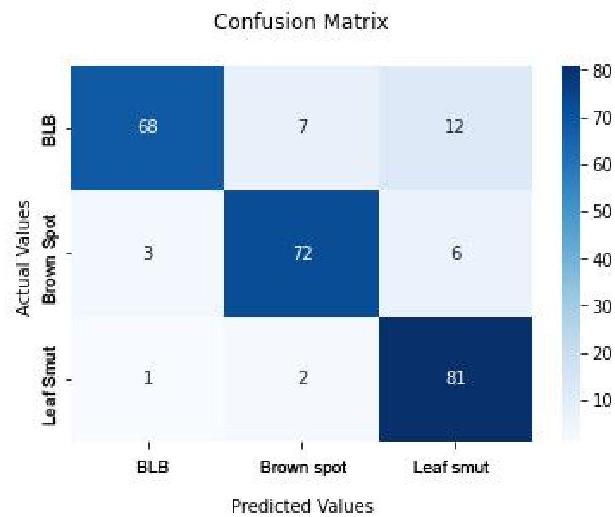

Figure 6.1. Confusion Matrix of Model with Attention

With the results of the confusion matrix showcased, proceeding with precision, recall, and F1-score. All the results within Table 6.1 all have values above 70%, it states that in any classification of the rice plant disease the CNN with Visual Attention is able to predict correctly with the Support column indicating how many features are used to evaluate the model. With the F1-score all above 85% then it can be stated that the model has high predictive power.

Table 6.1. Rice Leaf Recognition System Evaluation with Visual Attention

	Precision	Recall	F1-Score	Support
Bacterial Leaf Blight	0.94	0.78	0.86	87
Brown Spot	0.89	0.89	0.89	81
Leaf Smut	0.82	0.96	0.89	84
Accuracy			0.88	252

To compare the model, the proponents made a CNN without Visual Attention yielded an accuracy rate of 92.56%, in training, 86.51% in validation, and 93.25% in testing. Since the value is also greater than 70% then it is a model that is ideal for classification of rice plant diseases.

As for the confusion matrix in regards to CNN without Visual Attention yielded a more true positive relationship than CNN with Visual Attention in regards to actual and predicted labels of Brown Leaf Blight (BLB) and Brown Spot; therefore, it translates to the increase of the accuracy rate.

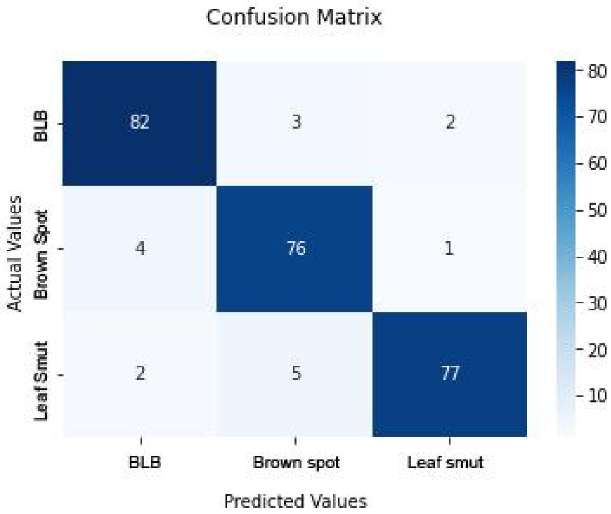

Figure 6.2. Confusion Matrix without Visual Attention

In Table 6.2 all of the values in regards to precision, recall, and F1-score have values above 70%. In comparison to the evaluation CNN with Visual Attention it is better throughout the entire metrics used.

Table 6.2. Rice Leaf Recognition System Evaluation without Visual Attention

	Precision	Recall	F1-Score	Support
Bacterial Leaf Blight	0.93	0.94	0.94	87
Brown Spot	0.90	0.94	0.92	81
Leaf Smut	0.96	0.92	0.94	84
Accuracy			0.93	252

To validate the accuracy of the CNN with and without attention the proponents used cross validation to use the whole dataset, automatically split the dataset per iteration, feed the data to the model, and get the average accuracy. The cross validation went through 10 splits and each split consists of 50 epochs. The results will be showcased in Table 6.3 and Table 6.4 for the comparison of the two models.

Table 6.3. Results of K-fold Cross Validation with Visual Attention

Mean Accuracy	91.67%
Standard Deviation	(+/-) 2.02%

Table 6.3. Results of K-fold Cross Validation without Visual Attention

Mean Accuracy	91.90%
Standard Deviation	(+/-) 1.64%

7. SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

Rice plant disease is a serious problem for the people as it leads to decrease in crop yield resulting in famine and decrease in profit annually. Having that as the core problem, the proponents made a Convolutional Neural Network with Visual Attention model to distinguish diseases present within the rice in order to diagnose and take preventive measures.

Based on the discussion of the result the Convolutional Neural Network without attention is the best in terms of mean average with an accuracy rate of 91.90% and worst case of 90.26%. However, in the best case scenario the standard deviation of Convolutional Neural Network with Visual Attention has an accuracy rate of 93.69%. In conclusion, Convolutional Neural Network without Visual Attention is the most versatile model to use for classification of rice plant disease while Convolutional Neural Network with Visual Attention is the one to be used if everything is ideal.

As for the recommendation, future researchers should add more dataset to the model to further test more rice plant disease which will increase the scope of the classification and will help decrease the chances of the model overfitting during the training period. Use deeper CNN models, ideally pre-trained where it is verified by professionals with the intention of being used in machine learning. For the preprocessing method should help the CNN model the ability to recognize the distinct features in diseases of rice plants

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