A WEB-BASED APPLICATION UTILIZING CONVOLUTIONAL NEURAL NETWORK (CNN) METHOD FOR DETECTING RICE PLANT DISEASES IN BUTUAN CITY, PHILIPPINES

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ABSTRACT: Currently, applications or tools for recognizing rice leaf diseases are one of the desires of farmers for the sustainability of rice planting and productions as rice plant diseases are one of the major challenges of farmers. Several bacterial, viral, or fungal diseases affect the rice plants causing reduction of rice productions. In the realm of rice plant disease recognition, there are several methods studied in the research community. In this study, the proponents developed a CNN-based model for recognizing common rice leaf diseases – Bacterial Leaf Blight, Bacterial Leaf Streak, and Rice Brown Spot. The CNN-based model is trained to recognize the three common rice leaf diseases using a database of rice plants with disease images. The developed model achieves a training accuracy of 93.67% and a validation accuracy of 91.25%. The developed model was integrated in a web application and reached an accuracy of 99.95% when tested on a set of independent rice plant disease images. In addition, several experiments using another set of images on the developed model in the web application for detecting rice plant diseases have been conducted and the developed model achieved recognition rates of 99.91%, 99.97%, and 99.94% for Bacterial Leaf Blight, Bacterial Leaf Streak, and Rice Brown Spot, respectively.

1. INTRODUCTION

1.1 Background of the Study

A paddy field or rice field is a flooded parcel of arable land used for growing semiaquatic crops, mostly notable rice and taro. It originates from the Neolithic rice farming of the Yangtze River basin in southern China, associated with pre-Austronesian and Hmong-Mien cultures [1]. Rice is Asia and the Pacific's staple food. In the Asia-Pacific region more than 90% of the world's rice is produced and consumed [2].

A pest infestation on rice plant has always resulting in enormous anxiety on farmers because of the damaged has been cost on their rice plants. For the past few years' farmers have experience a difficulty on identifying on what possible disease and pest the rice plant may have. Nowadays, they manually monitor the rice plant through picking up some examples and uses their hands to identify the possible disease and pest that attacks on it. For this reason, this study is conducted to develop a web-based application that can automatically detect the rice plant disease using only the image of the disease-stricken plant/leaf.

The Food and Agriculture Organization of the United Nation (UN) said that the common problem encountered by rice farmers were high cost of inputs, low price of palay, lack of capital, labor problem, lack of postharvest, facilities, irrigation system and the most common problem when the different pest's are destroying the production of rice during wet season, it causes leaf discoloration, stunted growth, reduced tiller numbers and sterile or partly filled grains, infected leaves turn greyish green and roll up[3]. As the disease progresses, leaves turn yellow to straw-colored and wilt, leading whole seedlings to dry up and die, and It attacks different parts of the plant: the collar, which can ultimately kill the entire leaf blade; the stem, which turns blackish and breaks easily (node blast); the neck of the panicle, where the infected part is girdled by a greyish brown lesion, or when severe, causes the panicles to fall over; or on the branches of the panicles which exhibit brown lesions when infected [4].

Convolutional Neural Networks (CNN) is an artificial network popular for pattern recognition in analyzing images. The researcher decided to develop an Application in Detecting Disease and Pests Infestation in Rice Plant Using Convolutional Neural Network (CNN) to identify particular pest attacks that might lead to disease and pest infested through image analysis and pest recognition.
This study can be used as aid for the users to monitor the condition of their rice plants and know the possible disease that to identify any has infested the leaf or plant. This study would be beneficial to the Department of Agriculture

(DA), farmers, and other possible users who need knowledge about their rice plants infestations, specially to the new comer farmers.

2. METHODOLOGY

2.1 Study Area

Butuan city is located at 8.9475° N, 125.5406° E, and it is an independent city and a highly urbanized city in the Caraga region, Philippines. Butuan City has a land area of 81,662 hectares (201,790 acres), which accounts for approximately 4.1 percent of the entire land area of the Caraga region. In terms of land use, the city now has farm areas (397.23 sq. kilometers), forestland (268 sq. kilometers), grassland/shrubland/pasture land (61.14 sq. kilometers), and other uses (90.242 sq. kilometers). The City has a total area of 4,295 hectares of Agricultural land and is expected to be planted with quality seeds.

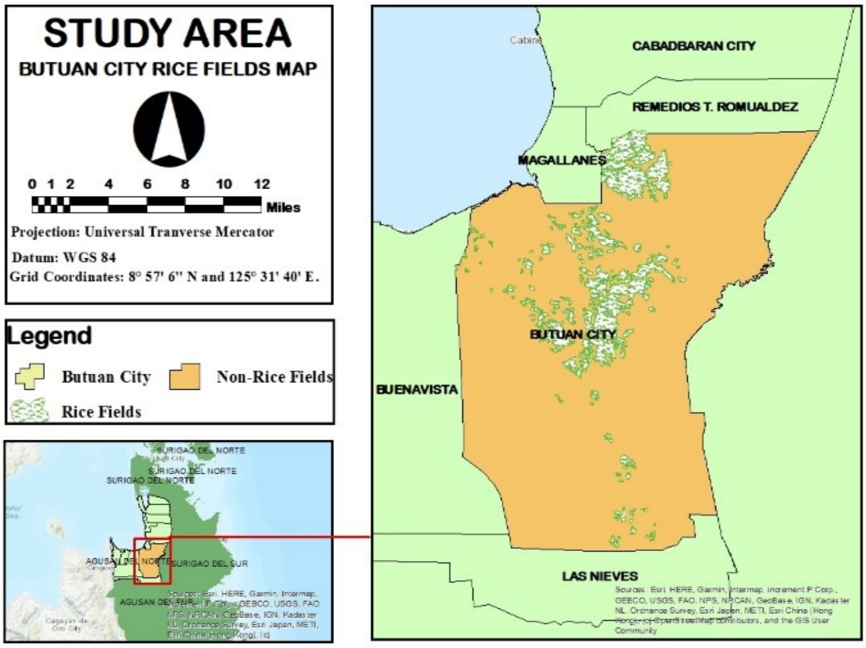

Figure 1 Study Area.

2.2 Methodological Flow Chart

The study seeks to find solutions to the growing problems of farmers in terms of rice disease identification tool by designing and developing a trained CNN-based model which classifies and detect the diseases through a web application, shown in Figure 2.

After designing and creating a suitable model for the rice plant disease identification and classification tool, Figure 6 shows that the web application platform is to develop a tool responsible for taking images in infected rice plants from a phone for data gathering. The image captured of the rice plant is collected and enter within the web application. It is the way to gather data from a plant to determine what types of diseases encountered in the rice plants. The image is enabling the farmers to collect data in the most in a simple way. After taking a picture, it is then to identify what types of diseases. Only the single captured image in real-time detection are pick to proceed for detection. The developed application will be the key for the farmers to identify the disease quickly. This step is to perform the actual capturing data from rice plants to the field. The CNN-based model will be the backend of the web application to classify the object. After the performing of disease identifier CNN-base model, CNN-based model classifies the type of disease and displays disease information during detection, like detected disease, test accuracy, and the marginal error. The result presented anytime, depending on if the application will be closed.

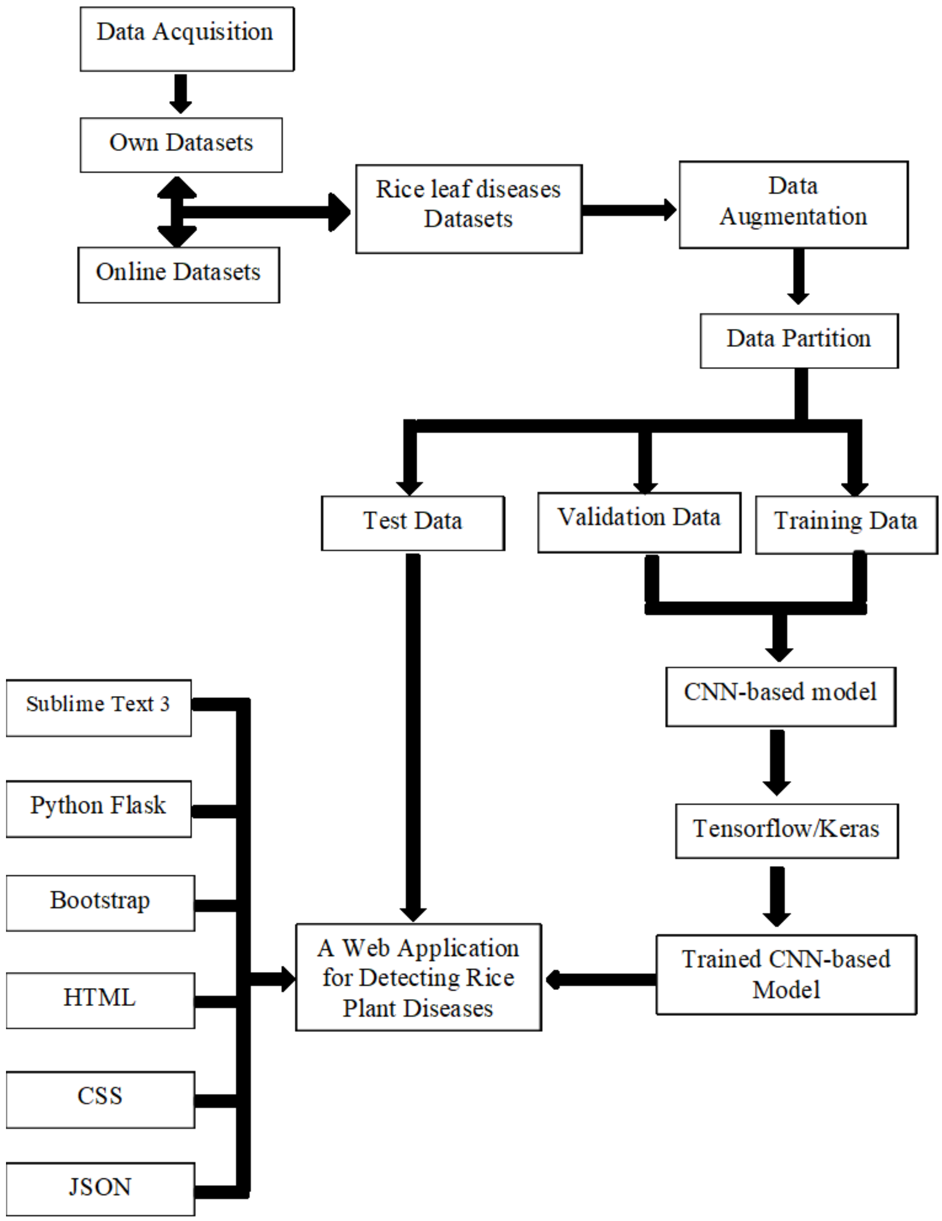

Figure 2 Flow chart in Designing a Web Application for Detecting Rice Plant Diseases using CNN Model

2.3 Data Gathering

Data acquisition is the process of gathering information on variables of interest from a range of sources, such as easily accessible and downloadable datasets from the internet and other reliable sources. The researcher intended to train the CNN-based model using a .jpg file with 180x180 pixel dimensions. The researcher intended to take an image in a well-lit area so that the system can provide an accurate result.

TensorFlow/Keras needs a hundred of images of an object to train good detection classifier. In preparation for the model, the training images should be random photos with a variety of backgrounds and lighting conditions, and some are partially obscure.

2.3.1 Field Data Gathering: The data was collected either by taking photographs on the rice fields or taking samples of the diseased rice leaves to be photographed conveniently. Also included are datasets from Butuan's City Agriculture Office.

2.3.2 Online Data Gathering: Due to the pandemic, obtaining photographs in the field was limited, and because the researcher's hometown lacks rice fields, the researcher must go from Sibagat to Butuan City merely to obtain images, which takes much time. As a result, the researcher decided to gather data from the Google and Kaggle teams via the internet.

2.4 Data Augmentation

A total of 135 original RGB colored images of three common rice leaf diseases are upgraded, including Bacterial leaf blight, Bacterial leaf streak, and Rice brown spot. A lack of training data is a significant hindrance to constructing effective deep learning models, such as CNN-based models for rice leaf disease detection. We need more data to ensure the durability of the neural network-based model and broaden the model's functional diversity. The researcher uses image data augmentation to enhance the dataset with minor distortion [5] [6]. The model's generalization is improved because of this data improvement. The researcher utilizes 45, 45, and 45 original RGB images of Bacterial leaf blight, Bacterial leaf streak, and Rice brown spot, respectively, to produce the augmented data and then use three types of augmentation approaches which are rotation, flipping, and brightness/contrast [5] [6]. Table 6 summarizes the statistics for the augmented dataset. The researcher rotates the photos by 90 degrees, -90 degrees, and 180 degrees, respectively, to supplement the data [5] [6]. The researcher also uses flipping to enhance data (horizontal and vertical) and lastly use brightness/contrast to augment data [5 [6]. For this purpose, the researcher uses Photoshop to apply the data as mentioned earlier augmentation strategies. Figure 3 depicts some examples of augmented photos with various data enhancements.

Table 1. Dataset's descriptions of rice leaf disease recognition.

Class	Number of Images	AUGMENTATION TECHNIQUE							TOTAL Augmented Images
		ROTATION			FLIPPING		Brightness/Contrast		
		90^{o}	-90^{o}	180^{o}	Horizontal	Vertical	Brightness (30%)	Contrast (30%)	
Bacterial leaf blight	45	45	45	45	45	45	45	45	315
Bacterial leaf streak	45	45	45	45	45	45	45	45	315
Rice brown spot	45	45	45	45	45	45	45	45	315

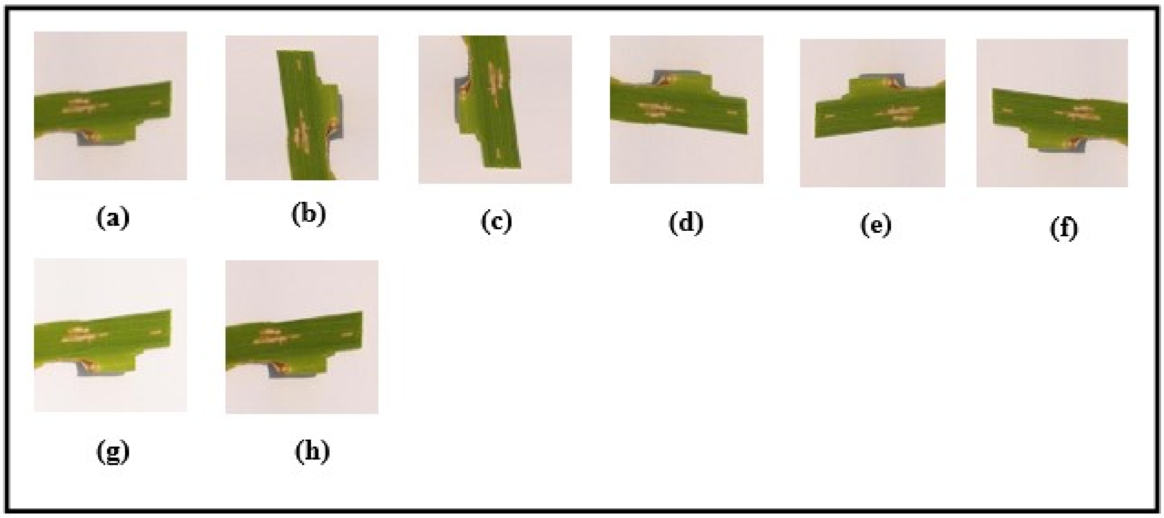

Figure 3 Augmented images of rice leaf diseases: (a) original Bacterial leaf blight image; (b) rotated with 90^{o} Bacterial leaf blight image; (c) rotated with -90^{o} Bacterial leaf blight image; (d) rotated with 180^{o} Bacterial leaf blight image; (e) flipped horizontally Bacterial leaf blight image; (f) flipped vertically Bacterial leaf blight image; (g) brightened Bacterial leaf blight; and (h) Contrasted Bacterial leaf blight.

2.5 Data Partition

Data partitioning is the formal process of defining which data subjects, data occurrence groups, and data attributes are required at each data site. It is an organized procedure for assigning data to data sites inside the same shared data architecture. The researcher divided the 1170 RGB colored 180x180 sized images of three common rice leaf diseases: Bacterial Leaf Blight, Bacterial Leaf Streak, and Brown Spot. As indicated in Table 7, the researcher utilized 864 of the data for training, 216 for validation, and 90 images of a diseased rice plant for the testing.

Table 2 Datasets Partition

CLASS	No. of Training images	No. of Validation images	No. of Testing images
BLB	288	72	30
BLS	288	72	30
RBS	288	72	30
TOTAL	864	216	90

2.6 CNN-Based Model for Rice Leaf Disease Recognition

The researcher proposes a custom CNN-based model for recognizing rice leaf diseases. The model is designed with a depth of 10 layers. These are input layer, convolution layer 1 (Conv2d), max-pooling layer (max_pooling2d), convolution layer 2 (Conv2d_1), max pooling layer 2 (max_pooling2d_1), convolution layer 3 (Conv2d_2), max pooling layer 3 (max_pooling2d_2), two dense layers (Dense1 and Dense2) and an output (SoftMax) layer as shown in Fig. 13 for an input image of size $w \times h$.

2.6.1 Field Data Gathering: The input layer of the CNN-based model was fed by an RGB image of size $w0 \times h0$, where w0 is the width and h0 is the height of the image, respectively.

2.6.2 Convolution Layers: The primary objective of a convolution layer is to find local conjunctions of features from previous layers and map their presence to a feature map. The researcher uses three convolution layers and various filters in the model to get the output feature maps. As a result, these maps save information about where the feature appears in the image and how well it fits the filter. As a result, each filter is spatially trained in terms of the volume to which it is applied, and each filter recognizes specific properties from the rice leaf disease image.

The researcher uses the nonlinear activation function ReLU to quickly allow complex relationships in the data to be learned. In the model, the researcher uses three convolution layers, namely Conv2d, Conv2d_1, and Conv2d_2. The researcher uses 16, 32, and 64 filters for Conv1, Conv2, and Conv3 layers. Table 8 illustrates the model parameters of these layers for an RGB image of size 180×180 and 3×3 filters.

2.6.3 Pooling Layers: In a CNN-based model, pooling plays a vital role by reducing variance and computation complexity, resulting in fewer learning parameters. It performs a down-sampling operation along with the spatial dimensions and reduces the dimensions of the feature map. Furthermore, it summarizes the feature that appears in a portion of the feature map generated by the convolution layer. Therefore, the rest of the operations are performed on summarized features that make the model more robust to variations in the location of the rice leaf disease images' features. In the model, the researcher uses three pooling layers, namely Max_Pooling2d, Max_Pooling2d_1, and Max_Pooling2d_2. Table 8 illustrates the model parameters of these pooling layers for RGB images of sizes of 180×180 and $2 \times$ two pooling layers.

2.6.4 Dense Layers: The output of the final max Pooling layer is flattened into a one-dimensional vector to be fed into a fully connected dense layer. This layer produces a one-dimensional vector M of size 128, fed into the second fully connected dense layer to produce a one-dimensional vector M' of size four (4) shown in Table 2.

2.7 Training the Model and Classification of Rice Leaf Diseases

In the customized CNN-based model, the deep features of rice leaf diseases are extracted and used in the identification model for rice leaf disease recognition. A CNN-based model's activations translate detailed information in an input rice leaf disease image into a more abstract representation as the image progresses through the deeper layers of the model, and they also summarize the most relevant characteristics of the image. Figure 14 shows the visual representations of a sample rice leaf image in each of the convolution and pooling layers of the model, with the convolution and pooling layers being the most visible. Deeper and more accurate (summarized) information is then employed as a feature, and the model's softmax layer is used to classify the information. In order to train the model, the researcher feeds the images through it in batches to learn and optimize the network parameters in the convolution, pooling, and dense layers, which summarize the features into a 1x128 vector. These features are then passed through another dense layer, which results in a 1x4 vector being produced. After that, the vector is transferred to the softmax layer, which uses it to classify an image of rice leaf disease into the appropriate class for that disease. Through a series of training images, which the researcher refers it as epochs, the researcher validates the model and the related parameters, and then through a series of validation images. As the loss function of the model, the researcher employs the term "Sparse Categorical Cross-Entropy".

2.8 Web Application Software Components

Software Components are utilized in the high-level software architecture of an Application Provider to capture the primary software pieces used to deliver the application.

Table 3 Software Components

Specifications	Recommended Requirement
Front-end	Bootstrap, CSS, HTML, and JSON
Back-end	Python Flask, Tensorflow/Keras, and GPU
IDE	Sublime Text 3

2.9 Validation

Agriculture officials from the Department of Agriculture and the Butuan City Agricultures Office conducted research and validated their findings on diseases affecting rice crops. Bacterial Leaf Blight (BLB), Bacterial Leaf Streak (BLS), and Rice Brown Spot (RBS) were the diseases documented.

Another set of images of the rice plant diseases were taken and used as datasets for the validation of the results of the image classification or the disease identification of the tool. Validation data is used to get optimal hyper-parameters for preventing the overfitting of the model.

3. RESULTS AND DISCUSSION

3.1 Scientific Generalization

During the requirements gathering and analysis phase, the researcher validated the effectiveness of the proposed application. The researcher gathered information on how to cater to rice plant problems with less effort and convenience. The researcher formulated a solution to help the farmers identify what disease that their rice plant has. The researcher formulated the knowledge analysis in order to enlighten the possible features of the application. From that, the researcher predicted all the possible features with the help of the information gathered. The researcher tested and verified the system developed and validated the train datasets. During the testing of the web application, the employees of the Department of Agriculture said that the system is sound, particularly when it comes to disease detecting. In terms of detecting the developed system, the employees said that the system is more valuable if it would detect symptoms.

This chapter describes the whole actual situation as the system develops. Below are the discussion of the results and the interface of the developed Web Application for Detecting Rice Plant Diseases using Convolutional Neural Network (CNN) based model.

3.2 Hyper-Parameters of CNN-Based Model

During the training phase of the model, the researcher utilizes sparse categorical cross-entropy as the loss function. When it comes to training and validation accuracy, the researcher only runs the model for 50 epochs because no additional improvements are detected. The loss function is optimized with the help of the Adam optimizer. The researcher uses 16, 32, and 64 3x3 filters in the Conv1, Conv2, and Conv3 layers in this study, respectively. 2x2 max pooling in the pooling layers of the model by default. The number of epochs and batch size in the experiment are set to 50 and 150, respectively, as the default values.

3.2.1 Effects of Epochs: The proposed CNN-based model is trained with a variable number of epochs up to a maximum of 50 when normal parameters. Because no additional improvements in the model's training and validation accuracy can take the best-tuned epoch in this situation is 50. The validation loss is substantially comparable to the training loss in the third and fourth epochs of the training process, as shown in Fig. 18. However, the validation accuracy is greater than the training accuracy at that stage, as seen in Fig. 19. Furthermore, the precision of training and validation data is deteriorating. Validation loss and training loss increased between the 11th, 12th, 13th, and 14th epochs, but both measures decreased in the latter scenario. The validation loss and training loss are continually decreasing from the 32nd to the 50th epochs, while training accuracy and validation accuracy are highest. The precision of training is still developing at the moment. Based on researcher findings, the model is trained to the 50th epoch and then stopped.

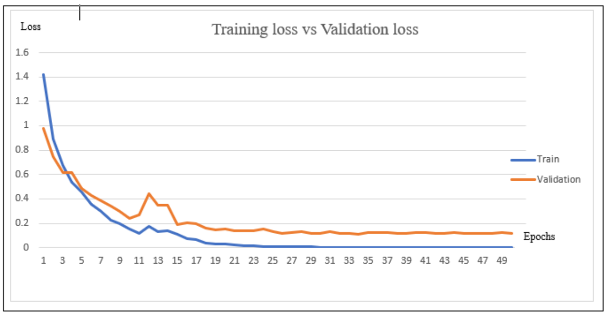

Figure 4 Training loss and Validation loss

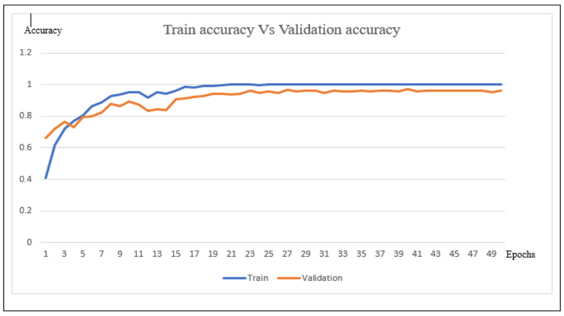

Figure 5 Training accuracy and Validation accuracy

3.2.2 Effects of Batches: The size of a batch has a significant impact on how well a model learns. The researcher uses batch sizes of 150 and 200 in the CNN-based model to ensure that the model runs smoothly. Table 12 shows how these batch sizes affected the model when different parameter settings were used. Table 12 demonstrates that when the batch size was set to 150, the model works best under the default conditions, consistent with the researcher's observations.

Table 4 Effect of Filters, Pooling(s), Epochs, and Batches on CNN-based model

Convolutional layers				Pooling layer		Epochs	Batches	ACCURACY		
Filter	Number of Filters			Pooling	Size			Train	Valid.	Test
	Conv 2d	Conv2d _1	Conv2 d_2							
3X3	16	32	64	Max	2X2	50	150	93.67%	91.25%	99.95%
3X3	32	64	128	Max	4X4	100	200	87.33%	85.21%	90.27%

3.2.2 Effects of Filters: Conv2d, Conv2d_1, and Conv2d_2 are the three convolution layers in the CNN-based model. To test the performance of different filters and the number of filters in the convolution layers with the 3x3 kernel filter, the researcher uses 16, 32, and 64 filters for 50 and 150 epochs and batch size, respectively, and 32,64, and 128 filters for 100 and 200 epochs and batch size, respectively. As indicated in bold in Table 12, the model achieves the best training, validation, and test accuracies in the Conv1, Conv2, and Conv3 layers, respectively, for 16, 32, and 64 filters.

3.2.2 Effects of Filters: The researcher uses maximum pooling to evaluate the CNN-based model's performance. Pooling2d, Pooling2d_1, and Pooling2d_2, with pooling sizes of 2x2 and 4x4, are the three pooling layers that follow each convolution layer in all circumstances.

3.3 Rice Disease Identification and Classification Using Web Application

In this chapter, we will see the results with its corresponding accuracy and marginal error using the developed Web Application for Detecting Rice Plant Diseases Using Convolutional Neural Network (CNN-based model). Sample results of the rice plant leaf disease identification are shown in the following figures.

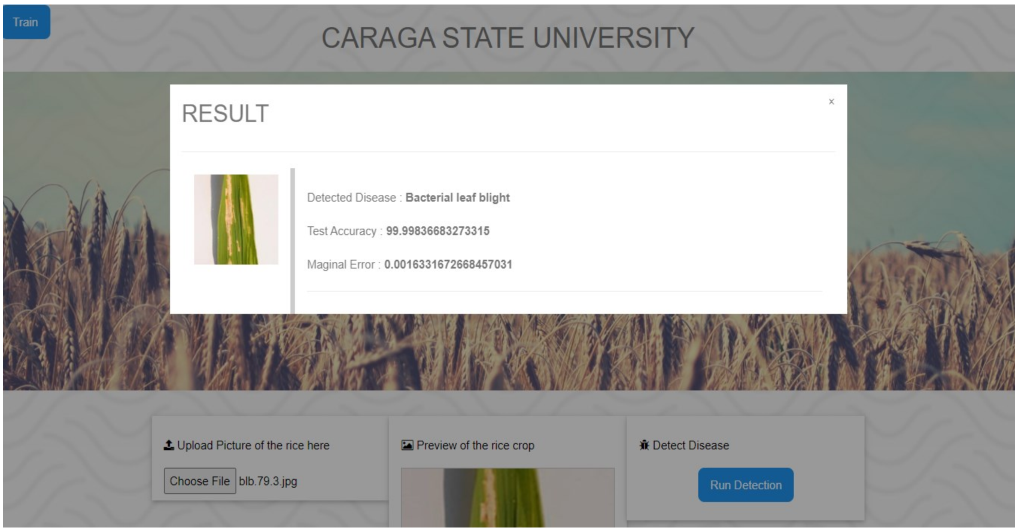

Figure 6 Detected Bacterial Leaf Blight

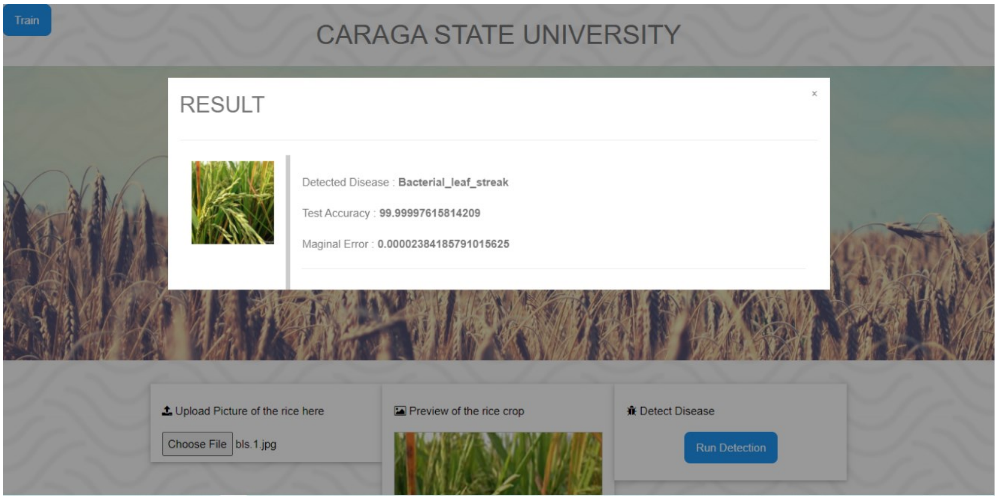

Figure 7 Detected Bacterial Leaf Streak

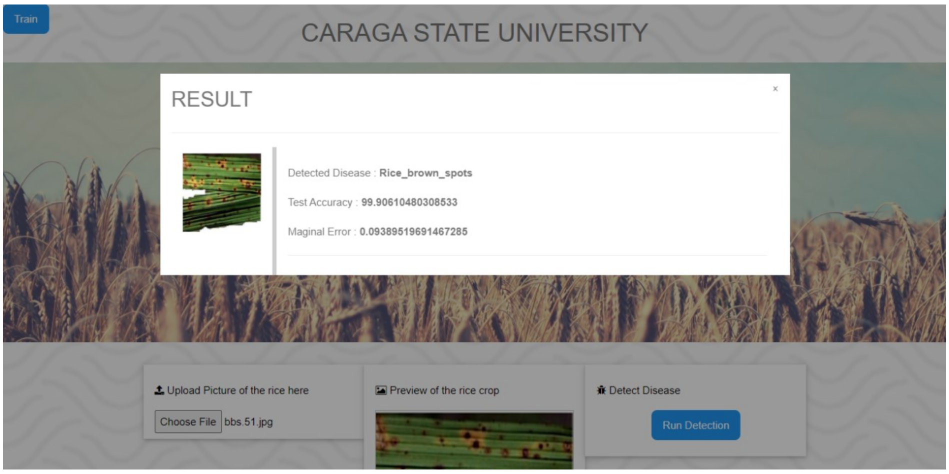

Figure 8 Detected Rice Brown Spot

The figures depict the classification results obtained through the use of a web application. By applying the trained CNN-based model to the web application using the Flask environment, the researcher obtains the following results. The figures show how the web application detects and displays the results of various rice diseases, together with the associated accuracy and marginal error, which can and detected using the web application.

3.4 Graphical User Interface (GUI)

As part of the research, front-end tools such as bootstrap create the web application's design and functionality. These front-end tools contain HTML, CSS, JSON, JavaScript, and the web application through a browser to display the web application. The researcher chose Python flask for the back-end tool, a web application framework that covers the fundamentals of URL routing and page rendering and other features are shown in Figure below.

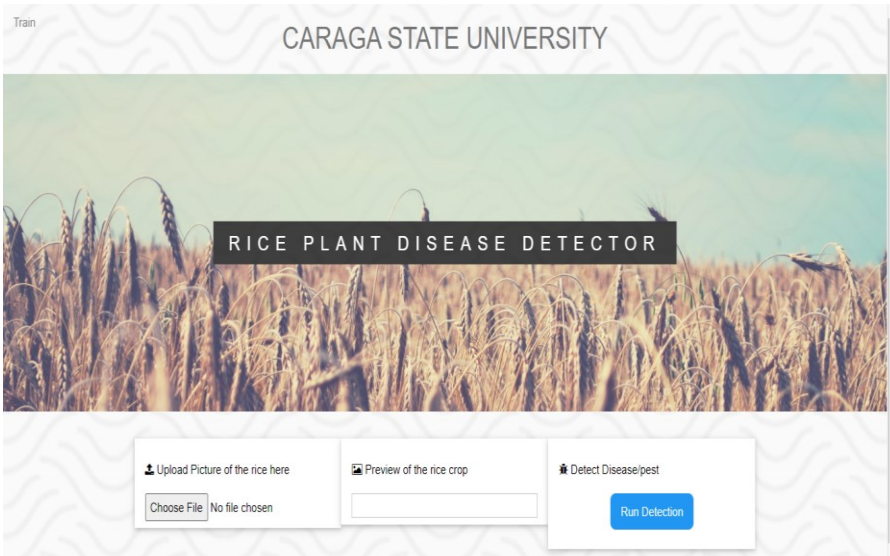

Figure 9 Rice Plant Leaf Disease Detector Tool Graphic User Interface

4. CONCLUSIONS AND RECOMMENDATIONS

4.1 Conclusions

The researchers developed a web application combined with convolutional neural networks to detect and identify rice plant diseases. The application will be used in conjunction with convolutional neural networks (CNN). It also assists farmers in reducing the pressure and burdens associated with some of the challenges they confront while monitoring the state of a rice crop over a period and days. In real-time, it allows the farmers to be easily identified.
In this research, the researcher proposed a unique CNN-based model that can categorize three common rice leaf

diseases often discovered in Butuan City. They can be classified using machine learning techniques. This model distinguishes rice leaf diseases in various image backdrops and captures situations, including bright sunlight. Using independent test images, this model obtains an accuracy of 99.9454 percentage.

Therefore, the researchers had met the study's objectives, which led to successfully developing A Web Application for Detecting Rice Plant Diseases in Butuan City using Convolutional Neural Network (CNN). Also, the application successfully performed its intended functions and features. The application was indeed helpful to the Department of Agriculture in this technological era. It emphasizes the importance of the application by identifying diseases on a rice plant. It took a great deal of difficult work and commitment, yet the researcher figured out how to achieve the study that prompts helping individuals in need.

4.2 Recommendations

The following are the recommendations that the researchers would like to suggest to have further improvements and enhancements of the studies relating to A Web Application for Detecting Rice Plant Diseases in Butuan City using Convolutional Neural Network (CNN).

- to try other CNN models;
- to improve the user interface;
- to add more disease information;
- to display the other diseases that is not detected on the application interface;
- to add more datasets for training and validation;

In addition, because of the reduced amount of network parameters in this model, it is efficient in terms of memory storage. In spite of the improved accuracy, the researcher hopes to increase the model's dependability and robustness by testing it on diverse datasets from different geographical regions. Furthermore, because the classification accuracy is an inadequate representation of the majority of real-world tasks, the researchers will also consider other interpretable CNN-based models that convey features in a way that is understandable to the public and from which diseases will be classified.

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