CONVOLUTIONAL NEURAL NETWORK-BASED IMAGE CLASSIFICATION FOR IMPROVED COCONUT DISEASE IDENTIFICATION

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Abstract

Coconut production is a vital source of income for the Philippine economy; thus, early detection of diseases is critical to improving the production capacity of coconut farmers. This project explores the use of deep learning technologies and computer vision to develop a model that can identify caterpillars, leaflets, drying leaflets, flaccidity, and yellowing in coconut trees. Specifically, we designed a deep 2D-Convolutional Neural Network (CNN) that can predict disease and pest infestations with high accuracy. The CNN was trained using a supervised deep-learning algorithm, which resulted in the five categories being predicted with an accuracy rate of 99% for yellowing and 100% for caterpillars, leaflets, drying of leaflets, and flaccidity, respectively. The proposed model has the potential to be a reliable diagnostic tool for effectively detecting diseases and infestations in coconut, supporting disease management programs in agriculture. As such, it is recommended that further research be conducted to integrate this technology into existing disease management programs for coconut farming in the Philippines.

Keywords: *coconut disease, convolutional neutral network, image processing, diagnostic tool*

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1. Introduction

The Philippines' coconut industry is very vital to the country's economy. In comparison to the 4.08 million metric tons produced at the same time last year, the production of coconuts grew to 4.12 million metric tons from July to September 2022, a rise of 1.0% (Philippine Statistics Authority, 2022). Infestations of insects and diseases could impede production growth, reduce the yield of the coconut crop, have an impact on related industries, and threaten the livelihoods of individuals who depend on the coconut economy. Infestations and diseases that afflict coconut trees most frequently in the central Philippines include caterpillars, leaflets, drying of leaflets, flaccidity, and yellowing (Datt *et al.*, 2020). Some regions in the country suffer from high rates of disease dissemination; fortunately, other sites do not show increases in incidence. Moreover, proper diagnosis requires time and effort for the experts to examine, identify, and classify every disease and infestation in a coconut field (Prathibha *et al,* 2019; Datt *et al*., 2020). Thus, the augmentation of technology may be needed to address the aforementioned problems.

To predict disease and pest infections, the deep 2D-convolutional neural network (CNN) that was specifically created is trained (Singh *et al*., 2021; Abdullahi *et al.,* 2017). The Artificial Intelligence Enabled Coconut Tree Disease Detection and Classification (AIE-CTDDC) paradigm for intelligent agriculture will result from this (Maray *et al.,* 2022; Yamashita *et al.,* 2018; Zhu *et al.,* 2018). In a smart farming environment, the AIE-CTDDC technique is utilized to classify coconut tree diseases to boost crop output (Singh *et al.,* 2021; Maray *et al.,* 2022). In addition, a drone equipped with a camera interface and the NVIDIA Tegra System on Chip (SoC) is advised as a component of a precision agriculture strategy to discover numerous pests in coconut plantations (Chandy, 2019; Yamashita *et al.,* 2018). Thus, for the identification of unhealthy and pest-affected plants, taking pictures and processing the data using deep learning algorithms will be easily done. The deep learning method makes use of a database of sample pests. The machine learning algorithm for artificial intelligence (AI) can also learn unsupervised lessons from unstructured visual data (Singh *et al.,* 2021; Maray *et al.*, 2022).

The main objective of this study is to develop an automated system that can accurately identify diseases and pest infestations in coconut trees. To achieve this goal, the research compared the pre-trained deep learning algorithm models using a Convolutional Neural Network (CNN) and developed an optimized deep learning model that can effectively identify infections from collected images. Additionally, the study investigated the effective methods for accurately identifying the infected regions within an image. The ultimate aim of this research is to improve the accuracy and efficiency of disease identification in coconut trees, and integrate the deep learning model into a web platform to provide a user-friendly interface for quickly identifying and diagnosing caterpillars, leaflets, dried leaflets, flaccidity, yellowing disease, and infestations.

2.0 Methodology

Coconut disease classification was done using a convolutional neural network (ConvNets/CNN).

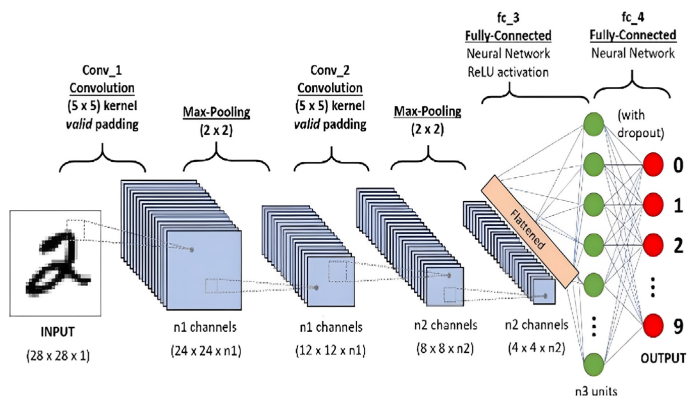

Figure 1. Convolutional Neural Network (CNN) Architecture

A CNN (Figure 1) is a Deep Learning technique that can take an input image, assign various objects and elements values (learnable weights and biases), and differentiate between them. Comparatively, the pre-processing time for a CNN is much lower than for other classification methods. Unlike simple techniques where filters are hand-engineered, CNN can learn these filters and their attributes (Yamashita *et al.,* 2018).

The structure of the visual cortex served as inspiration for the construction of a CNN, which resembles the human brain's interconnected network of neurons. Individual neurons can only respond to stimuli in the restricted region of the visual field known as the Receptive Field. There are numerous overlapping areas like this that fill the full visual field (O'Shea & Nash, 2015).

2.1. Input

Step – 1 Data Gathering and Pre-processing

Images of coconut tree diseases and insect infestations were

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obtained in this project (Table 1).

Table 1. Classification of Coconut Diseases

Caterpillars	Leaflets	Drying of Leaflets	Flaccidity	Yellowing

The dataset used in this study was collected from multiple sources, comprising authentic images obtained from coconut plantations in Surigao del Sur. For training, validation, and testing, sets of photographed coconut tree leaves were created and separated into sections. The remaining thirty percent (30%) of the obtained photos were used for testing, leaving seventy percent (70%) for training and validation. Three-colored channel (RGB) matrix of pixel data to the images was used in classifying the collected images, whether the coconut tree leaves have caterpillars, leaflets, drying of leaflets, flaccidity, and yellowing in the inputs of the model.

Table 2. Coconut Disease Image Data Distribution

Class	No. of Samples	70% Trainings and Validation	30% Testing
Caterpillars	991	693	298
Leaflets	795	557	238
Drying of Leaflets	1,078	755	323
Flaccidity	1,069	749	320
Yellowing	1,084	759	325
Total	5,017	3,513	1,504

The gathered data set consisted of 5,017 images and was divided into 5 classes: 991 for caterpillars, 795 for leaflets, 1,078 for drying of leaflets, 1,069 for flaccidity, and 1,084 images for yellowing. It was then partitioned accordingly since 70% was needed for training and validation, and 30% was for testing. The final data sets for training and validation were 693 for caterpillars, 557 for leaflets, 755 for drying of leaflets, 749 for flaccidity, and 759 for yellowing. On the other hand, the final datasets for testing are 298 for caterpillars, 238 for leaflets, 323 for drying of leaflets, 320 for flaccidity, and 325 for yellowing.

2.2. Feature Learning

Step – 2 Convolution

The photos were delivered to the feature extraction module after convolution was applied. In the process of turning the input data into a set of features, the proponent extracted crucial information from the input image. Features of many different kinds, including color, texture, forms, and edges, are possible. To improve accuracy in the suggested approach, the leaf color of coconut trees was taken into account. Consequently, the incoming picture data was colored, and each channel was given its own filter/kernel. The picture was considerably larger than the filter, therefore,, the proponent had to hover over each channel of the image matrix value and multiply the filter/kernels matrix value by each channel of the image matrix value until the complete image was traversed. The convoluted features were formed after the data for each channel were averaged and added with a bias (Maray et al., 2022).

Step 3 - Normalization

Normalization significantly shortened the model's training time. For this stage, the proponent used the Rectified Linear Unit (ReLU) as an activation function (Agarap, 2019). The feature map's value was adjusted by setting all negative pixel values to zero. As a result, training time was reduced without compromising the image's characteristics. The formula for the rectified linear unit (ReLU function) is as follows:

$$f(x) = \max \{0, x\}$$

Step 4 – Pooling

By pooling layers, the feature maps' dimensions were reduced. It consequently reduced the amount of computation performed within the network and the number of parameters that must be learned. The pooling layer condenses the features that are present in a specific area into a feature map that was produced by a convolution layer. The information was summarized using the following procedures rather than the precisely positioned features produced by the convolution layer. The input photos of coconut tree leaves, make the model more resilient to changes in feature position. A sort of pooling called max pooling chooses as many elements as it can from the feature map area that the filter has covered. The outcome of the max-pooling layer was a feature map with the most observable characteristics from the previous feature map. The objects shown in the filter-reduced region of the feature map were averaged using average pooling. In contrast to maximum pooling, which returns the most prominent feature in a feature map patch, average pooling returns the average of all the features in the feature map patch (O'Shea & Nash, 2015; Yamashita *et al.,* 2018).

2.3. Classification

Step 5 – Flatten

The pooled feature maps' resulting 2-dimensional arrays were all flattened into a solitary, lengthy continuous linear vector. The flattened matrix was given as input to the fully connected layer to categorize the image (O'Shea & Nash, 2015; Yamashita *et al.,* 2018).

Step 6 – Dropout

In a dropout layer, the contributions of all neurons to the layer below are preserved, while the contributions of particular neurons are canceled out. Some of the properties of the input vector were removed by applying a drop-out layer. Additionally, certain hidden neurons in a hidden layer may be removed using this method (O'Shea & Nash, 2015; Yamashita et al., 2018).

Step 7 – Fully Connected

Feedforward neural networks serve as the foundation for the Fully Connected Layer. Fully Connected Levels are the topmost network layers. Before being sent as input, to the fully connected layer, the output of the last pooling or convolutional layer is flattened. As seen in Figure 2, the last layer uses the softmax activation function (instead of ReLU) to assess the chance that the input corresponds to a particular categorization depending on whether the coconut tree is healthy or afflicted (O'Shea & Nash, 2015; Yamashita *et al.,* 2018; Agarap, 2019). Finally, Figure 3 displayed the likelihood that each categorization applied to the object in the image.

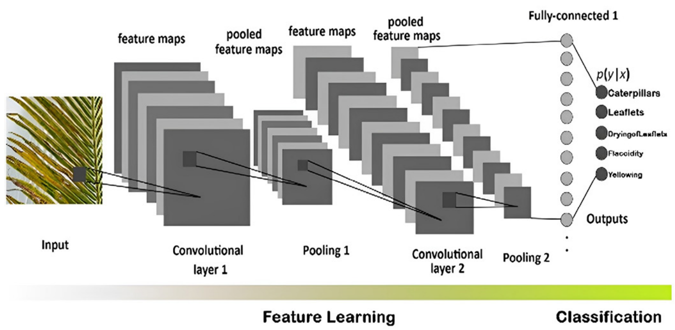

Figure 2. Internal Block of CNN Architecture

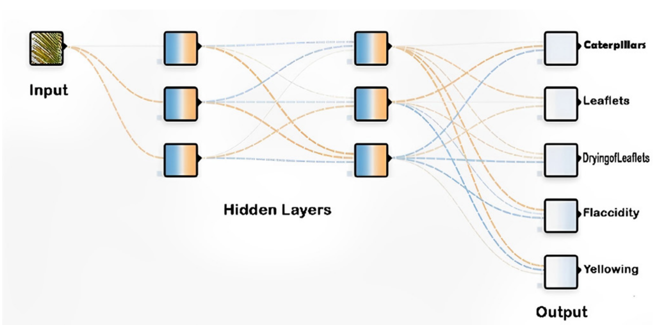

Figure 3. Neural Network

2.4. Procedure

Step 8 – Model Training Procedure

The model was trained using a supervised training method. Visually picking and classifying samples from a picture is necessary to provide statistical measurements that can be applied to the complete image. Two popular techniques of identifying the complete image using the training data are maximum likelihood and minimal distance (Yamashita *et al.,* 2018; O'Shea & Nash, 2015).

Step 9 – Model Testing Procedure

A confusion matrix was used to test the concept. The columns of the confusion matrix correspond to the output classes of the neural network, and the rows of the matrix to the goal classes in the data set. Positive means were recognized, and negative means were discarded in binary classification. True positive (TP) was successfully detected, and false positive (FP), the neural network's output was a probability in general. The categorization is thus determined by the decision threshold. The decision threshold is set to 0.5 by default. The output shown above is positive, whereas the output listed below is negative (O'Shea & Nash, 2015; Yamashita *et al.,* 2018).

3. Results and Discussions

The model's performance evaluation results are presented in this section. It displays an overview of the data set as well as how the data is divided into training and validation and testing sets. Moreover, it utilized and followed the recommended CNN architectural model to detect coconut disease and infestation.

Table 3. Confusion Matrix

		Predicted Class	
		P (Positive)	N(Negative)
Actualization	P (Positive)	TP (True Positive)	FN (False Negative)
	N (Negative)	FP (False Positive)	TN (True Negative)

Table 4 shows the result of the training and validation accuracy in different classes.

Table 4. Training and Validation Accuracy per Class

Class	Accuracy (%)	Samples
Caterpillars	100	693
Leaflets	100	557
Drying of Leaflets	99	755
Flaccidity	99	749
Yellowing	100	759

In the class of caterpillars, leaflets and yellowing obtained a 100% accuracy with 693, 557, and 759 samples respectively. On the other hand, 99% accuracy was observed in the class drying of leaflets and flaccidity with 755 and 749 samples respectively. Thus, the class drying of leaflets and flaccidity attained 1 false negative prediction result during training and validation. Other classes did not have any false positive and false negative prediction results during the training and validation (Table 5).

Table 5. Training and Validation Confusion Matrix

	Prediction				
Class	Caterpillars	Leaflets	Drying of Leaflets	Flaccidity	Yellowing
Caterpillars	693	0	0	0	0
Leaflets	0	557	0	0	0
Drying of Leaflets	0	0	754	0	0
Flaccidity	0	0	0	748	0
Yellowing	0	0	0	0	759

Table 5 displayed the training and validation matrix. A confusion matrix can be used to derive the following equation in the accuracy level:

$$\text{Accuracy} = \frac{104 + 84 + 113 + 112 + 114}{529} \times 100 = 99.62\%$$

Table 6 shows the testing accuracy while Table 7 shows the confusion matrix. In testing the accuracy per class, caterpillar, leaflets, drying of leaflets and flaccidity obtained a 100% accuracy with 298, 238, 323, and 320 samples respectively. Conversely, yellowing attained 3 false positive predictions resulting in a 99% accuracy while the other classes do not have any false positive and false negative prediction results during the testing (Table 7).

Table 6. Testing Accuracy per Class

Class	Accuracy (%)	Samples
Caterpillars	100	298
Leaflets	100	238
Drying of Leaflets	100	323
Flaccidity	100	320
Yellowing	99	325

Table 7 displays the training and validation matrix. A confusion matrix can be used to calculate the accuracy level with the following equation:

$$Accuracy = \frac{298 + 238 + 323 + 320 + 322}{1,504} \times 100 = 99.80\%$$

Table 7. Testing Confusion Matrix

	Prediction				
Class	Caterpillars	Leaflets	Drying of Leaflets	Flaccidity	Yellowing
Caterpillars	298	0	0	0	0
Leaflets	0	238	0	0	0
Drying of Leaflets	0	0	323	0	0
Flaccidity	0	0	0	320	0
Yellowing	0	0	0	0	322

The majority of the most recent agricultural advancements produced by research are intimately related to both production and each other. With the intention of increasing agricultural production, improving crops, preventing and preparing for plant diseases, and modern, automated, and mechanized agriculture and agro-industry (Zhu *et al.,* 2018). Deep learning methods like CNN would be a useful tool in solving future problems in agriculture, especially in the diagnostics of coconut and other crop diseases and infestation. Abdullahi *et al.* (2017) presented that CNN needs a lot of training data to function effectively. However, if the dataset is not very huge, image augmentation can be used to amplify a limited dataset. A deep learning (DL) model's classification accuracy is improved by augmenting old data rather than obtaining new data (Schmidhuber, 2015). In reality, applying the data augmentation technique allows for the avoidance of overfitting problems and great accuracy. The potential of DL applications in agriculture is forecastable. Furthermore, rather than sticking with a single strategy, it is possible that future developments in DL for agriculture may incorporate a number of theories and strategies. According to the metadata analysis, DL applications in agriculture are growing from the Recs counts (Zhu *et al.,* 2018). However, they are widely dispersed and pursue very distinct scientific objectives. It signifies that there are still more potential and challenges in the sector and that more work is required.

4.0 Conclusion

The use of Convolutional Neural Networks (CNN) in classifying coconut diseases and infestations has shown promising results. The model achieved high training and validation accuracy of 99% to 100% and testing accuracy with a very low loss in different class categories. Computer-aided devices and reliable data are essential factors that can help coconut farmers improve their performance in early disease and infestation diagnosis. Image processing systems can aid farmers in modernizing their farming systems and improving production outputs. The next step will involve gathering a large number of high-quality photos of various crop diseases and pests, followed by model optimization, adjustment, and extension to other crops to increase their applicability. Finally, the integration of the model into a mobile application will facilitate easy and non-destructive detection of coconut diseases and infestations in real-time.

Further research is recommended to optimize the performance of the CNN-based image classification model by increasing the size and diversity of the dataset, exploring different network architectures, and fine-tuning the hyper-parameters. The practicality of implementing the model in real-world settings and developing user-friendly interfaces should also be considered to facilitate its use by farmers and other stakeholders. This can include the development of mobile applications or web platforms that provide real-time disease identification and management recommendations based on the model's output. Finally, the impact of the model on coconut farming practices and its potential to contribute to the sustainability of the industry should be evaluated to guide future research and development efforts.

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