Convolutional Neural Network Model for Cacao Phytophthora Palmivora Disease Recognition

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***Abstract*—Cacao, scientifically known as Theobroma cacao, is a highly nutritious food and is extensively utilized in multiple sectors, including agriculture and health. Nevertheless, the agricultural sector encounters notable obstacles as a result of Cacao disease such as pod rot, predominantly attributed to the Phytophthora genus. The objective of this work is to conduct a comparative analysis to determine the most effective machine-learning technique for the detection of P. palmivora infection in Cacao pods. Few studies have delved into this topic previously, but this study focuses in utilizing a little larger dataset, achieving better model, and attaining higher accuracy. A total of 2000 images of cacao pods, both healthy and disease-infected were collected. Subsequently, the images were subjected to manual classification by a domain expert based on the discernible presence or absence of the disease. The study examined six machine learning algorithms, specifically Naïve Bayes, Random Forest, Hoeffding Tree, Multilayer Neural Network, and Convolutional Neural Network (CNN). The CNN model had 99% level of accuracy, the highest among the five machine learning algorithms in the testing phase. The methodology has the potential to significantly advance sustainable agricultural practices and disease management. To enhance the model's recognition capabilities, additional datasets encompassing a broader range of Cacao varieties is necessary.**

Keywords—Machine-learning; Convolutional Neural Network; detection of P. palmivora

I. Introduction

Cacao (Theobroma cacao), also known as “superfood” or “the food of the gods”, has gained full attention by farmers, researchers, and even health enthusiasts [1]. Consumption of this product worldwide is estimated to be over 4.5 million tons annually and is still growing. The innovation of new products that requires cacao as an ingredient has increased the demand for such. Examples of these are not limited to cosmetics, pharmaceuticals, food and beverages, and health food supplement. The Philippines' geolocation and the humid temperature make it conducive for cacao production to flourish and possibly attenuate poverty; thus, local farmers' interest scaled up, and exporters push for a more productive cacao industry that can participate in the worldwide supply competition [2].

However, the yield of cacao production is affected by several diseases, with pod rots as the most common adverse conditions of the tree. Phytophthora, a genus of straminipilous organisms (formerly classified as oomycetes), is responsible for the devastating black pod rot, the most widespread disease affecting cacao crops. Depending on environmental conditions, this disease can lead to annual losses of up to 90% in pod production. The entire plant can become infected, causing severe damage [3].

Traditionally, diagnosing infections relies on human experts. However, aside from the high cost and time-consuming nature, this approach can be impractical due to the scarcity of experts and potential geographic barriers, especially if the farm is remote. In such cases, the disease might affect a large number of pods. To address these challenges, researchers are turning to machine learning techniques for plant disease recognition as a viable solution.

Although few studies have previously explored this topic, this research aims to use a larger dataset to develop a better model and achieve higher accuracy.

Moreover, this study aimed to apply different machine learning techniques to the dataset for comparative analysis; and evaluate the accuracy of the models in recognizing the incidence of P. palmivora disease on Cacao pods. The dataset covers the cultivars Criollo, Forastero, and Trinitario; and the common variety of Cacao found at the Molave hill of the Visayas State University, Leyte, Philippines.

This research could play a crucial role in the early recognition of P. palmivora disease, which would allow for the prompt application of treatments. Consequently, this would lead to an improvement in Cacao production. The method proposed in this research represents a potentially significant advancement in eco-friendly and sustainable farming techniques, as well as in disease control within the Cacao industry. By promoting such practices, this research supports the United Nations' Sustainable Development Goals related to agriculture and innovation. Adopting these advanced methods would not only enhance crop yields but also foster more sustainable and environmentally responsible agricultural practices.

II. Review of Literature

A number of studies have already been conducted to recognize pests and diseases in plants and fruit trees using computer vision for the past years. These endeavors have greatly helped the agricultural sector in achieving better harvest to feed the world.

A. Non-Cacao Plants / Trees

The study by [4] proposed a system for identifying leaf diseases using Complete Local Binary Pattern and K-means

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clustering methods. The system's true positive and false positive rates were also measured. The authors suggest that their system will enable farmers to detect significant diseases and pest infestations in crops, thereby allowing them to take necessary preventive measures. On the other hand, [5] employed image processing and fuzzy logic classifier to detect prevalence of P. palmivora disease on jackfruit. The model effectively recognized and classified the infection with an accuracy rate of 90%. Also, [6] enhanced the application of convolutional neural network on detection of tomato fruit common physiological diseases by data augmentation technique, by adding grayscale processor and foreground extractor components, and by utilizing k-means clustering algorithm. The mean Average Precision of the model was 97.24%. Similarly, [7] created a strawberry grading system based on 3 attributes namely: color, size, and shape. The developed technology used K-means clustering method, multi-attribute Decision Making Theory, and a single-chip-microcomputer (SCM). The size processing error is below 6%, its color marking precision is 88.8%, the shape categorizing accuracy is 90%, and the strawberry fruit grading takes 3s. Relatively, [8] implemented a hybrid system using Artificial Neural Network (ANN), Fourier descriptors (FD) and spatial domain analysis (SDA) for identifying fruits and sorting. The 3 different angles of camera inclination were used in the testing and evaluation. The experimental results showed a 99.10% accuracy rate. Also, [9] developed a system to detect and classify Pomegranate fruit diseases employing k-means clustering segmentation, GLCM method, and Artificial Neural Network. Based on the evaluation, the system yielded an accuracy rate of 90%. The author in [10] implemented a system that identifies the deformity in orange fruits utilizing multi-class SVM with K-means clustering for disease classification and Fuzzy logic to calculate the level of infection severity. The system assessment outcome revealed 90% accuracy. Another study by [11] integrated advanced defect segmentation techniques and texture, combined color, and shape-based features with the Histogram of Oriented Gradients (HOG) feature descriptor and a Bagged Decision Trees classifier. This approach successfully distinguished between healthy and defective apples, achieving an accuracy rate of 96%. Also, [12] employed an enhanced fuzzy C-means (FCM) algorithm and the marked-watershed algorithm to improve the extraction of cucumber leaf spot disease from images, even under complex backgrounds. The study evaluated 129 cucumber disease images from a vegetable disease database, revealing an average segmentation error of just 0.12%. This method offers a reliable and robust segmentation approach for the classification and grading of cucumber diseases in agriculture, with potential applicability to other imaging-based agricultural assessments.

B. Cacao Tree

The author in [13] utilized the K-means algorithm in conjunction with a Support Vector Machine (SVM), leveraging color information in the L*a*b* color space as features to recognize and segment the affected areas. The study outcome revealed an 89.2% accuracy rate. The method can be employed in enhancing the performance of the SVM classifier particularly in differentiating clearly the healthy reddish color of the cacao pod from a disease of the same color. On the following year, Tan et al. developed a mobile app called Automated Tool for Disease Detection and Assessment for Cacao (AuToDiDAC) that automates the detection, separation, and examination of the level of Black Pod Rot (BPR) infection in the fruit. K-means clustering algorithm and Support Vector Machine (SVM) were still utilized. Fifty (50) pod images were used in training the system while 10 were used in testing. The app showed only an accuracy mean of 85%. The author in [14] implemented another mobile app to identify cocoa diseases on cocoa plant utilizing digital image processing methods. The canker infection on cocoa pods was emphasized as a sample disease. Ten (10) images were utilized in training while 20 for testing the automated identifier. The experiment revealed a 100% accuracy in identifying the existence of canker disease on the pods. In the testing phase, the user had to feed infected pods only, though the article did not mention the type of infection. Another study detecting the condition of cacao pods by [15] got a 94% accuracy. In relation, [16] built a MobileNet model to identify pod diseases which yielded an 86.04% accuracy. In 2024, [17] developed a deep learning-based computational model to identify cocoa pod diseases with an accuracy of 34%.

This study aimed to achieve a higher accuracy rate in identifying the P. palmivora infection occurrence on cacao pod and would explore the following machine learning techniques: Naive Bayes Classification, Decision Stump, Random Forest, Hoeffding Tree, Multilayer Neural Network, and Convolutional Neural Network.

III. METHODOLOGY

The research framework adapted is shown in Fig. 1. Each phase of the framework is an integral part in the success of this endeavor:

1) Image acquisition: The dataset was captured using Vivo Y91 with 13 MP rear camera with an image resolution of 3120 x 4160 pixels. Collection of sample images was done between 10:00 in the morning until 3:00 in the afternoon at the cacao farm of the Visayas State University, Philippines. The camera was positioned 9 cm away from the cacao pod for both infected and not infected pods. The presence of P. palmivora on the Cacao pods was the focus of this study. These images were then manually classified by the domain expert, Dr. Arsenio D. Ramos of the VSU Horticulture Department.

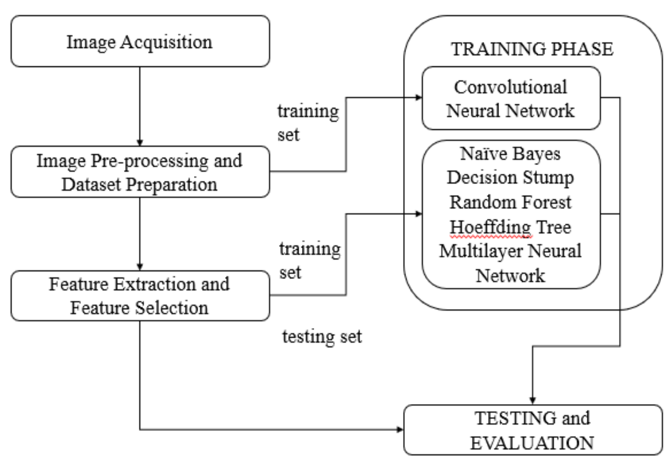

Fig. 1. Conceptual framework of the study.

The classified images were grouped and further divided into three subsets: 80.00% for training and 20.00% testing. The distribution of images among the classes in each subset is shown in Table I.

TABLE I. DATASET FOR THE STUDY

Class	Training	Testing	Total
Healthy	800	200	1000
Unhealthy	800	200	1000
Total (Dataset)	1600	400	2000

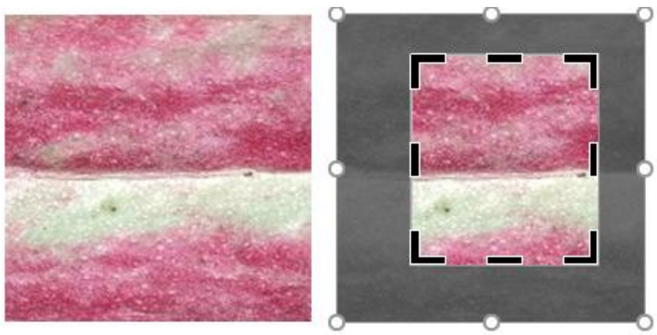

Fig. 2. Cropped image.

2) Image Pre-processing: The sample images for the training and testing phases were cropped to 150 x 150 pixels dimensions emphasizing the cacao texture. This applies to both healthy and infected datasets. Fig. 2 shows the cropping of an image of an infected pod.

These datasets were intended for use in all six (6) machine learning techniques.

3) Feature extraction and feature selection: Features such as color, shape and texture were extracted to characterize images using Haralick algorithm. Feature selection was carried out to determine the most suitable features for training the model and for attaining the best classification.

4) Model training: Training procedures were performed using different supervised machine learning algorithms that recognizes patterns and relationships from labeled training dataset. The different algorithms are the following: Naive Bayes Classification, Decision Stump, Random Forest, Hoeffding Tree, Multilayer Neural Network, and Convolutional Neural Network (CNN).

5) Model testing and evaluation: The generated models were verified to predict the untrained dataset. The performance of the models was evaluated and compared using the basic metric, the accuracy.

IV. RESULTS AND DISCUSSION

The Convolutional Neural Network (CNN) model exhibited outstanding performance by obtaining a 99% accuracy rate in detecting and classifying data throughout the testing phase, as evidenced in Table II, which presents a comparative comparison of six distinct machine learning algorithms. The CNN model demonstrated superior performance compared to the other tested techniques, indicating its effectiveness and reliability for the given task.

A. Convolutional Neural Network (CNN)Architecture

Fig. 3 illustrates the overarching architecture of the convolutional neural network employed in this study. The network consists of a sequence of interconnected layers that have been tailored to obtain features from the input image, decrease dimensionality, and to finally categorize the input data. More precisely, the architecture employs a sequential model structure, consisting of three convolutional layers. The initial layer is assigned a total of 32 filters, the succeeding layer has 64 filters, and the third layer has 128 filters.

Following each convolutional operation, a Rectified Linear Unit (ReLU) activation function was applied. Subsequently, max pooling layers with a 2x2 filter size and a stride of 2 are employed to down sample the feature maps, effectively halving their dimensions. The resulting pooled feature maps were then flattened into a singular vector, facilitating their transition into the fully connected (dense) layers for further processing.

The first dense layer is comprised of 128 nodes, with each node being triggered by a Rectified Linear Unit (ReLU) function. In addition, a batch normalization layer is included to normalize inputs for the following layers, while dropout regularization was used to reduce overestimation by inhibiting complex co-adaptations during training.

Conversely, the output layer employs a softmax activation function with 2 units, allowing the model to predict the likelihood of each input belonging to one of the two distinct classes based on the highest probability assignment.

Table III illustrates the model's synthesis, showing the resulting output form and the parameters that were learned automatically throughout the training process. The calculation of parameters inside each layer follows the equation [18]:

Number of parameters = weights + biases

Where: weights = input maps × (filter size) × output maps

The initial convolutional layer, with a 3x3 filter, applied to an input image size of 150x150x3 (150 pixels wide, 150 pixels high, and 3 color channels), results in an output shape of 148. In this layer, 3 feature maps are used as input, while 32 feature maps are produced as output. This requires the use of 32 separate filters, each with dimensions of 3x3x3. By including a bias term for every attribute map, the total number of parameters adds up to 896.

TABLE II. MACHINE LEARNING TECHNIQUES COMPARATIVE ANALYSIS

Machine Learning Technique	Training Accuracy	Testing Accuracy
Naïve Bayes	75.31%	73.00%
Decision Stump	74.80%	68.70%
Random Forest	99.00%	89.00%
Hoeffding Tree	78.00%	77.25%
Multilayer Neural Network	86.25%	86.50%
Convolutional Neural Network	98.06%	99.00%

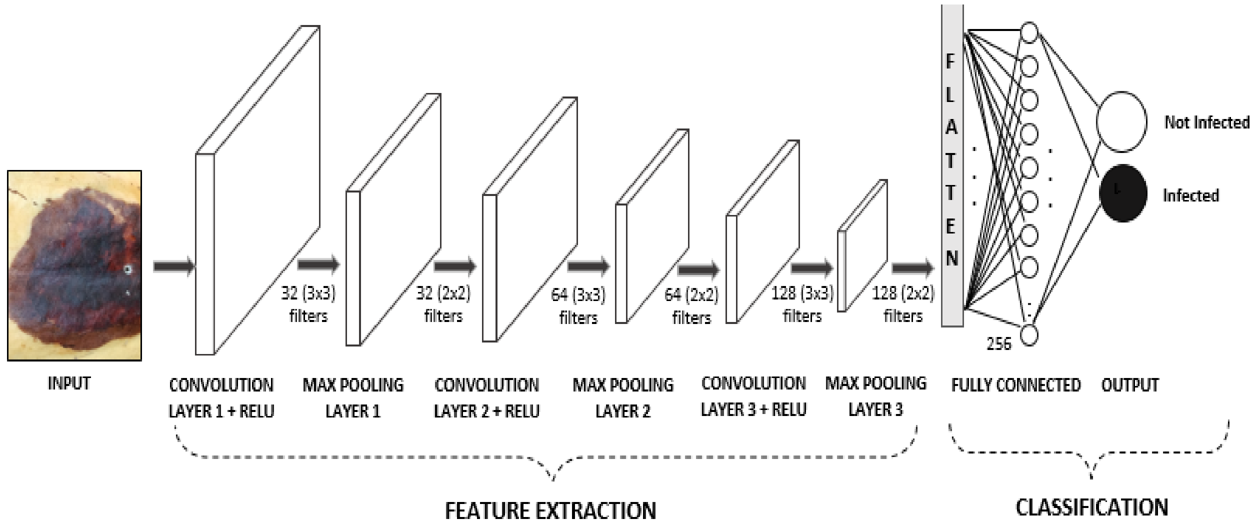

Fig. 3. CNN Architecture.

Consequently, the pooling layer conducts a straightforward substitution of a 2x2 neighborhood with its maximum value, thereby evading the inclusion of learnable parameters within this stratum.

When moving to the fully linked layer, the number of parameters is calculated by multiplying the number of input and output maps, and then adding an extra bias for each output. As a result, the two dense layers contain 73856 and 9470208 parameters, respectively.

Fig. 4 and Fig. 5 depict the visualization of model accuracy and loss per epoch, respectively. The line graphs indicate that the model was effectively learned, with consistent performance observed across both the training and validation datasets.

TABLE III. SUMMARY OF THE CNN MODEL

Layer (type)	Output shape	Param
conv2d_1 (Conv2D)	(None, 148, 148, 32)	896
activation_1 (Activation)	(None, 148, 148, 32)	0
max_pooling2d_1(Maxpooling2)	(None, 74, 74, 32)	0
conv2d_2 (Conv2D)	(None, 72, 72, 64)	18496
activation_2 (Activation)	(None, 72, 72, 64)	0
max_pooling2d_2(Maxpooling2)	(None, 36, 36, 64)	0
conv2d_3 (Conv2D)	(None, 34, 34, 128)	73856
activation_3 (Activation)	(None, 34, 34, 128)	0
max_pooling2d_3(Maxpooling2)	(None, 17, 17, 128)	0
flatten_1 (flatten)	(None, 36992)	0
dense_1 (Dense)	(None, 256)	9470208
activation_4 (Activation)	(None, 256)	0
dense_2 (Dense)	(None, 2)	514
activation_5 (Activation)	(None, 2)	0
Total params: 9,563,970 Trainable params: 9,563,970 Non-Trainable params: 0		

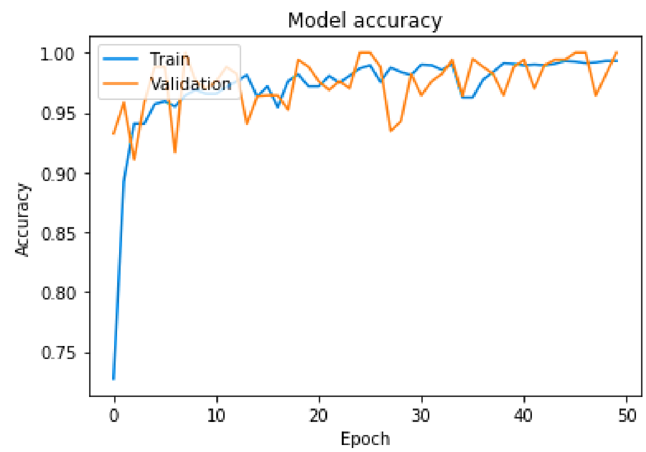

Fig. 4. The plot illustrating the training accuracy of the CNN model.

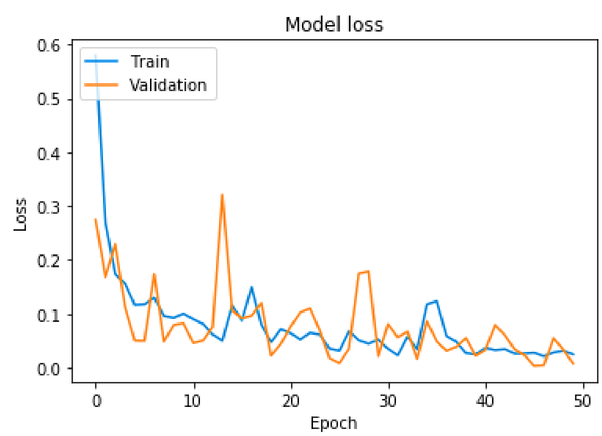

Fig. 5. The plot depicting the training loss of the CNN model.

V. CONCLUSION

This study successfully extracted color, shape, and texture features from digital images of cacao pods using the Haralick algorithm. These features were then partitioned and utilized to build and test classification models using various machine learning techniques, including Naive Bayes Classification, Decision Stump, Random Forest, Hoeffding Tree, and Multilayer Neural Network. Additionally, the same dataset was employed to develop a Convolutional Neural Network (CNN) model with different feature extraction method. Among the six models developed, the CNN model achieved the highest accuracy at 99%, outperforming the other five machine learning algorithms during testing. This methodology holds significant potential for advancing sustainable agricultural practices and disease management.

VI. Future Work

Cacao cultivation encompasses a wide range of varieties, each with its unique characteristics and susceptibilities to diseases and pests. Expanding the dataset to encompass more cacao varieties ensures its applicability across more diverse agricultural contexts, catering to the specific needs and challenges faced by farmers cultivating different varieties. Also, training a dataset with artificial lights at any time of the day or in the absence of natural light may be done. The CNN model may be integrated in mobile app so that intended users can try the system while inputs from them may be solicited to improve the modeling.

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