Cassava Disease Detection using MobileNetV3 Algorithm through Augmented Stem and Leaf Images

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Abstract*— As an agricultural country, the Philippines rely on agriculture as the backbone of its economy where one of the major crops produced is cassava. Its ease in cultivation, as well as its profitability, are some of the reasons why the said root crop considers to be one of the staple crops in the country. One of the factors that can negatively impact the growth and progress of the agricultural sector is the occurrence of diseases among plants. Managing the detection and spread of cassava disease relies on early identification in the field as the first step. The solution to this was the image-based detection methods, but they heavily rely on plant leaf analysis, leaving out other parts of the plant such as its stem to which disease may first manifest. To address such gaps, this research focuses on devising an image-based cassava leaf and stem disease detection system. Five (5) classes of leaf diseases and three (3) classes of stem diseases are considered in this study. The system used MobileNetV3 with dataset augmentation to create two models responsible for detecting cassava disease through the leaves and stems, respectively. The trained models underwent validation through data not used in the training process wherein the leaf and stem models attained accuracies of 93.20% and 90.80%, respectively, which offers and effective digital cassava disease detection.

***Keywords*— Cassava, disease detection, deep learning, MobileNetV3, data augmentation**

I. Introduction

One of the vital sectors in the Philippines serving as the backbone of the economy as well as the primary source of income among Filipinos living in rural areas is agriculture. In the Philippines, one of the major crops produced is cassava. Its ease in cultivation, as well as its profitability, are some of the reasons why the said root crop considers to be one of the staple crops in the country. However, one of the major concerns not just in cassava farming but in agricultural livelihood, in general, is the threat posed by various diseases. Some common diseases found in cassava plants are caused by fungal, viral, and bacterial organisms, and the manifestation of such conditions can be observed on leaves and stems. If not prevented, diseases in cassava plants could hamper the quality of growth and production in harvesting root crops, and worse, could result in total loss of the entire crop yield. With that, the early detection of plant disease is crucial to prevent the deterioration of plant quality and yield.

Managing the detection and spread of cassava disease relies on early identification in the field as the first step. Traditionally, identification approaches hinge on agricultural extension organizations and manual visual inspection, but are limited in most countries, cost a lot of human capital, and are expensive to scale up [1]. Other methods used to detect diseases on plants using images include case-based reasoning, spectral data, and Dempster Shafer method [2]. On the other hand, there are studies that used deep learning-based approaches in detecting diseases among plants, particularly on banana, tomato, rice, citrus, and cassava [3].

While traditional methods through manual visual inspection is still dominant in the country, the method falls into a subjective factor, as farmers and scientists rely on optical inspection. The solution to this was the image-based detection methods such as case-based reasoning, spectral data, and Dempster Shafer method, but they do not carry out the learning process on the dataset. To address this drawback, deep learning-based approaches through convolutional networks were applied. However, most of these methods heavily rely on plant leaf analysis, leaving out other parts of the plant such as its stem and roots, to which disease may first manifest. In such a situation, including the cassava stem when it comes to disease detection will offer new insights and correlations, through automated image recognition.

To address such gaps and concerns, this research focuses on devising an image-based cassava leaf and stem disease detection system using MobileNetV3 with augmentation. Specifically, the study aims: (1) to devise a system capable of detecting cassava diseases through the leaves and stem; (2) to enrich the dataset consisting of cassava leaf and stem images through data augmentation; (3) to use MobileNetV3 and train it through the augmented dataset; and (4) to validate the system by measuring its accuracy and detection performance using a validation dataset.

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The proposed system will contribute to more accessible methodologies in detection of diseases in plants, particularly cassava, through image processing that come with computers or smartphones. As cassavas being one of the major Philippine crops produced in the Philippines, devising such a system will help the country in achieving food security. Furthermore, the study will contribute to deep learning algorithms regarding the detection of cassava plant diseases using both leaf and stem images, as previous studies only focused on the former. A beneficiary of this proposed system is the Department of Agriculture, where it would provide an improvement on the detection accuracy and time of farmers. Lastly, having a reliable system capable of detecting diseases on plants will keep individuals who are cultivating cassava plants informed about the common diseases that commonly manifest on leaves and stems.

The study will focus on the detection of cassava plant diseases using leaf and stem images alone. With that, the determination of the cause of the disease will not be covered in the study. Furthermore, since the study focuses on detection, giving treatment to the affected plant will not be a part of the study. The study will not also cover the detection of diseases manifesting on parts of the cassava plant other than the leaf and stem. In providing training sets for the deep learning algorithm, data augmentation will be performed. The actual testing of the prototype will be done by collecting images from a cassava farm in Mansalay, Oriental Mindoro. Then, when validating the performance of the system, the diagnosis of an experienced cassava plant cultivator from the Bureau of Plant Industry will serve as the reference for the accuracy of classification of disease by the system. And in performing and simulating the program for the image processing part, the programming language Python will be used.

II. Review of Related Literature

Cassava is considered as one of the heavy sources of carbohydrates, key vitamins, and minerals among root crops [4]. Despite its low protein content, its weight of carbohydrate per unit area is measured to be significantly higher than other staple food crops when comparing under certain agro-climatic conditions.

In the Philippines, about 120,000 hectares of agricultural land is used for planting and cultivating cassava plants. In 2019, the country has accounted for a total volume of 2,630,800.28 metric tons of cassava produced [4]. Based from data gathered by the Philippine Statistics Authority, the average cost of cassava production in 2019 was P42,204.00 per hectare, with the average yield value per hectare was quantified at 11,834 kilograms which was priced at P97,623.00, displaying signs of profitability.

One of the factors that can negatively impact the growth and progress of the agricultural sector is the occurrence of diseases among plants. Plant diseases are grouped into two types: infectious and non-infectious. Infectious diseases are caused by organisms that may carry disease-causing microorganisms, and some examples of which include fungi, bacteria, virus, and even insects [5].

Cassava can be easily destabilized due to its vulnerability to diseases [1]. In monitoring the condition of plants, one of the parts that are typically checked is the leaf by assessing its surface details such as color, pattern, and texture [6]. However, for cassava, some diseases can manifest in parts other than leaves, such as stems and roots. The following diseases are some of the common types that can manifest in leaves and stems: cassava bacterial blight, cassava brown streak disease, cassava green mite, cassava mosaic disease, witches' broom or phytoplasma, as well as anthracnose.

Applying deep learning algorithms for plant disease and pest detection or classification have been a great concern for many researchers [7]. It is therefore an important research subject matter regarding computer vision, where it is used to acquire images and judge whether there are diseases or pests in those images. To some extent, computer vision-based detection of diseases in agriculture has replaced the traditional method of naked eye identification of these diseases [7].

MobileNet is a computer vision model designed to be used in mobile applications. Neural networks in mobile applications are steadily becoming ubiquitous, allowing for brand new device experiences [8]. The latest iteration, MobileNetV3 uses a combination of the layers from the prior versions to create the most effective model [8]. Moreover, this model has been applied to the detection of diseases of various plants such as bean leaf [9], grape leaf [10], and proper plant leaf diseases or PLD detection [11].

Although deep learning models have made significant progress in discriminative tasks through the advancement of deep network architectures, access to big data, and powerful computation, there is still much to improve regarding the generalization ability of these models [12]. Building reliable deep learning models require that validation errors must decrease together with the training errors, and data augmentation is an efficient method to meet such requirements. One of the most popular methods of data augmentation is through traditional affine and elastic transformations, which refers to creating new images by rotating, reflecting, zooming in and out, shifting, distorting, and changing the color of the image [13].

Augmenting the data allows for more comprehensive data points by increasing the amount of training data using data that is only available in the training dataset [14]. This therefore diminishes the distance between the training and validation data set [12].

III. Methodology

A. Conceptual Framework

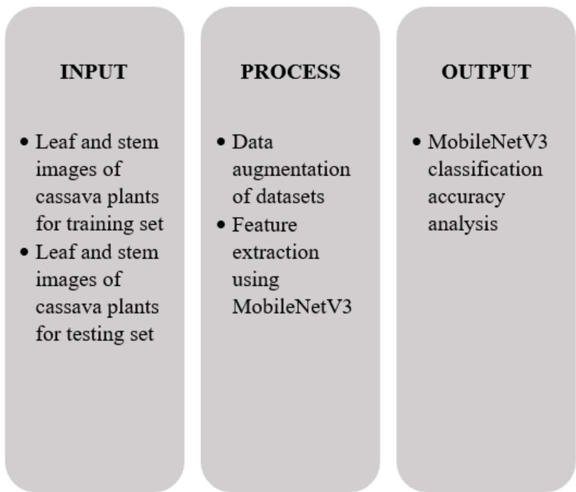

Fig. 3.1. Stages of research

The conceptual framework of the study is illustrated in Fig. 3.1. The inputs of the system will be the stem and leaf images of cassava plants, which are divided into two sets: training set and testing set. Then, the process comprises two parts: (1) augmentation of datasets to exponentially increase the dataset to be used for training of algorithm and testing of the system and (2) feature extraction of leaf and stem images of cassava plants using MobileNetV3 to classify the disease type. Lastly, the extracted data from the MobileNetV3 algorithm will undergo analysis to determine the accuracy of the system.

B. System Flowchart

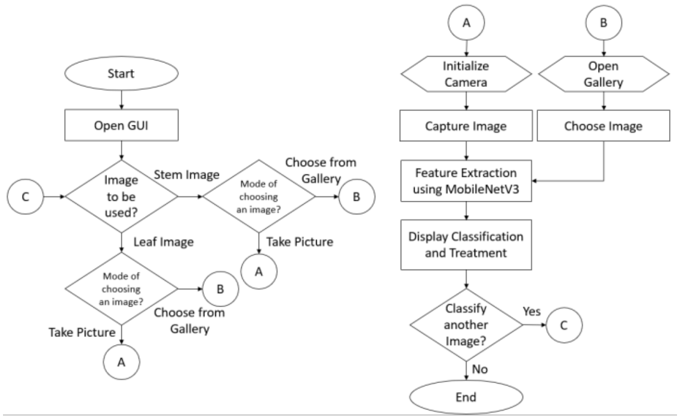

Fig. 3.2. System flowchart

In Fig. 3.2, the process regarding the detection of cassava plant disease through leaf and stem images begins with the initialization of the GUI where the user can decide whether to detect disease through leaf or stem images. Each choice is presented with two options, whether to use the camera to take the image or choose the image from the gallery. Upon capture or selection of the image, the trained model will then classify the disease in the image and specify a corresponding treatment. This ends the process of the system until another image is input to be classified.

C. System Development

1. Materials and Set-up

Table 1. Materials

Materials	Unit
Laptop	1
Android 13 Smartphone with 64-megapixel camera	1

Table 1 shows the materials used to build the system. The laptop is used to train the MobileNetV3 algorithm using Python before it is implemented within the graphical user interface, which is created through Android Studio. The smartphone is used to run the graphical user interface that displays the analysis of cassava plant disease using leaf and stem images. It runs on Android 13 operating system and is equipped with a 64-megapixel camera used to take pictures of cassava leaves and stems.

In the testing set-up, the application is run in the smartphone that was developed from the laptop using Android Studio. This gives the researchers the option to either take a picture of the plant using the camera or upload an image saved from its gallery. The distance between the phone and the cassava plant is estimated to be 1 to 2 feet to ensure the quality and coverage of the image. The subject is given a necessary amount of lighting to provide a clearer output on the capturing of the picture.

2. Graphical User Interface

Fig. 3.3. Graphical user interface

Fig. 3.3. shows the graphical user interface made in Android Studio. This includes the two ways in which the user can detect and classify diseases in cassava plants, which are by means of leaf and stem images. For both ways, the user is given an option to directly take a picture of the cassava leaf or stem using the camera of the phone or to upload a photo that is saved from the gallery of the phone. After selecting an image, the system prompts the disease classification together with the suggested treatment for the given disease that the user must perform which was validated by Senior Science Research Specialist Henry Acosta from the Depart of Agriculture, shown in Table 2.

Table 2. Cassava Disease and Treatment

Disease	Treatment
Cassava Mosaic Disease	Remove/destroy any showing symptoms. Infected plants should be uprooted.
Cassava Bacterial Blight	Remove or plow crop debris from soil after harvest; inter-crop with corn and melon; prune infected part.
Cassava Green Mite	Plant during rainy season for vigorous growth. Use foliar spray such as neem oil; inter-crop with other crops to reduce damage.
Cassava Brown Streak Disease	Remove and destroy any symptomatic plants as well as alternative hosts.
Witches' broom	Remove and destroy infected plants; disinfect tools and equipment between cuttings; remove all debris after harvest.
Anthracnose	Avoid using cuttings infected with cankers; destroy crop

	debris after the harvest.
Healthy	None.

D. Dataset Enrichment

1. Dataset Description

MobileNetV3 will be trained using the training dataset obtained from TensorFlow dataset which consists of leaf images of the cassava plant containing four classes of disease, namely: green mite (CGM), brown streak (CBSD), mosaic disease (CMD), as well as bacterial blight (CBB). The dataset also contains healthy images of the cassava plant. Overall, it consists of 7211 labelled images, split into three parts: the training set with 5772 images, a test set with 721 images, and a validation set of 718 images. A sample of some of the labeled images in the dataset is shown in Fig. 3.4.

Fig. 3.4. Sample images from cassava leaf dataset

However, the researchers seek to add another dataset focused on the stem part of the cassava plant as well as the introduction of two diseases, Witches' broom and anthracnose, that are prominent in the stem, in order to fulfill the second objective of this study. This will be done by obtaining stem images of the Cassava containing Witches' broom and anthracnose on the internet which will be further enriched through augmentation. The dataset consists of 749 labelled images, split into three parts: the training set with 574 images, a test set with 88 images, and a validation set of 87 images.

2. Dataset Augmentation

The images in the dataset will undergo changes to make them more diverse and improve generalization. Specifically, the brightness, contrast, saturation, hue, and crop of the images will randomly be changed. The images will undergo affine transformation, which includes rotating, reflecting, zooming in and out, shifting, distorting, and changing the color of the image [31]. TensorFlow provides a way to fine tune the dataset through augmentation.

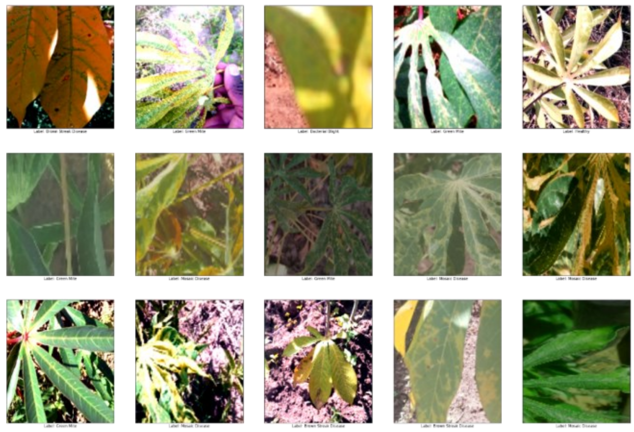

Fig. 3.5. Sample augmented images from cassava leaf dataset

Fig. 3.5 shows how the cassava leaf dataset can be randomly augmented to enrich the dataset and help in preventing overfitting. The training dataset will undergo random crop, resizing, brightness, contrast, saturation, and hue, while the testing and validation datasets will only undergo resizing and center crop.

E. Algorithm Training

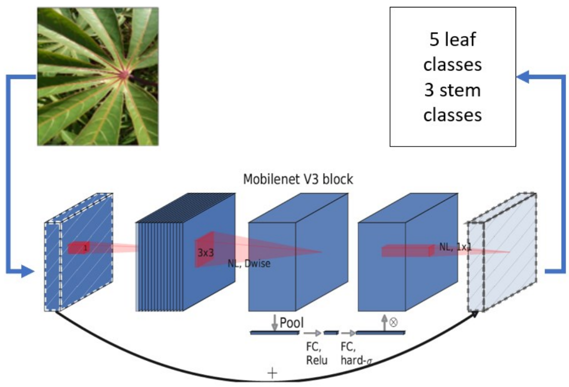

Fig. 3.6. MobileNetV3-Large process diagram

Fig. 3.6 shows the process diagram of MobileNetV3 with the cassava leaf at its input. The first block in the diagram 224x224x3 conv2d block which will preprocess the cassava leaf or stem image and resize it to 224x224x3. Then, the output of this block goes through a series of bottleneck blocks in order to compress features so they may fit in the available space. The next step in the process is another conv2d layer with 960 output channels before going under the process of pooling for generalizing features which were extracted from the preceding convolutional layer. Next, it undergoes a conv2d process again and converts the input into a 1x1x960 size before finally resizing it to a 1x1x1280 size through another conv2d layer whose number of output channels is 5 for the leaf model and 3 to the stem model.

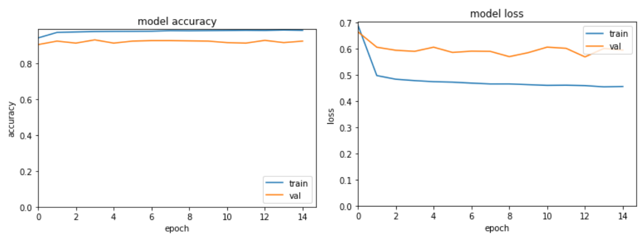

Fig. 3.7. Leaf model accuracy and model loss

Fig. 3.7 shows the leaf model accuracy and loss vs the number of epochs set at 15. The training resulted in an accuracy of 0.9848 with a test accuracy of 0.9248. meanwhile, the model achieved a training loss of 0.4565 and its test loss was at 0.5957.

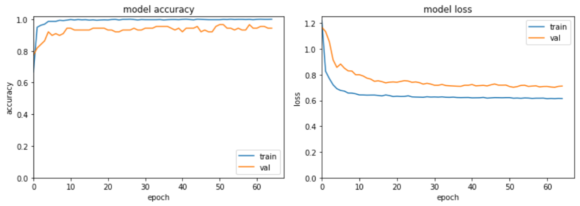

Fig. 3.8. Stem model accuracy and model loss

Fig. 3.8 shows the stem model accuracy and loss vs the number of epochs set at 65. The training resulted in an accuracy of 0.9971 with a test accuracy of 0.9432. meanwhile, the model achieved a training loss of 0.7113 and its test loss was at 0.6148.

IV. Results and Discussion

After the algorithm training, the two models were validated using the testing set wherein the set for leaf model consists of 721 images and the set for stem model consists of 88 images. Fig. 3.10 and 3.11 show the confusion matrix of the leaf and stem disease classification, respectively.

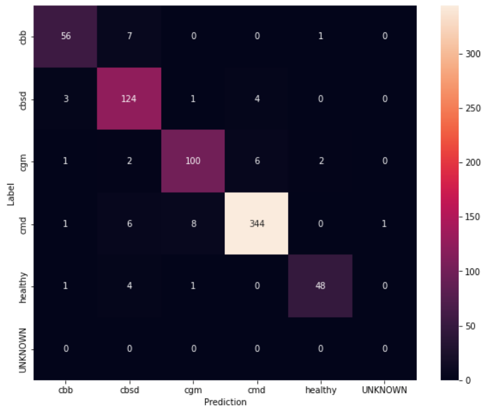

Fig. 4.1. Leaf model confusion matrix

The confusion matrix of the leaf validation dataset is shown in Fig. 4.1. The trained leaf model reached an accuracy of 0.9320 and a loss of 0.5695.

Table 3. Internal System Classification Validation for Leaf

Type	Number of Trials	Number of Matched	Accuracy
Healthy	54	48	**88.89%**
Bacterial Blight	64	56	**87.50%**
Brown Streak Disease	132	124	**93.94%**
Green Mite	111	100	**90.09%**
Mosaic Disease	360	344	**95.56%**
Total	**721**	**672**	**93.20%**

The tabulated results of the system validation for the leaf model can be seen in Table 3. The testing set consisting of 721 images comprises 54 images of healthy cassava leaves, 64 images of bacterial blight, 132 images of brown streak disease, 111 images of green mite disease, and 360 images of mosaic disease. During the system validation, the mosaic disease images garnered the highest accuracy, resulting in 95.56%, followed by brown streak disease and green mite with 93.94% and 90.09%, respectively, and by healthy as well as bacterial blight, which garnered a result of 88.89% and 87.50%, respectively. In total, the system classification validation for leaf images had a total of 672 images matched, which is equivalent to 93.20% accuracy.

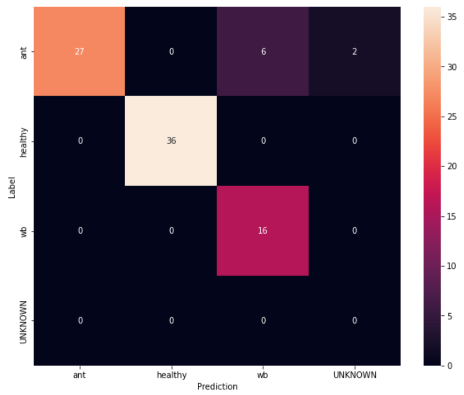

Fig. 4.2. Stem model confusion matrix

The confusion matrix of the leaf validation dataset is shown in Fig. 4.2. The trained leaf model reached an accuracy of 0.9080 and a loss of 0.8258.

Table 4. Internal System Classification Validation for Stem

Type	Number of Trials	Number of Matched	Accuracy
Healthy	36	36	**100.00%**
Anthracnose	35	27	**77.14%**
Witches' Broom	16	16	**100.00%**
Total	**87**	**79**	**90.80%**

Table 4 shows the tabulated results of the system validation for the stem model. The testing set consisting of 87 images comprises 36 images of healthy stems, 35 images of anthracnose, and 16 images of witches' broom. Both 36 healthy images and 16 witches' broom images garnered a 100% accuracy while the anthracnose images garnered 27 out of 35 matching trials, resulting in a 77.14% accuracy. In total, the system classification validation for stem images had a total of 79 images matched, which is equivalent to 90.80%

Table 5. System Evaluation Results

Parameter	Leaf Classification	Stem Classification
Number of Trials	721	87
Accuracy of Model	0.9320	0.9080
Accuracy from Previous Study	0.8122	0.8122
P-Value	1.1271e-37	0.9954e-3
Level of Significance	0.05	0.05

Table 5 presents the values for different parameters involving system evaluation of leaf and stem disease classification. To test whether the accuracy of the two models have a significant difference over that of the previous study, z-test for proportions is performed with a 5% confidence interval. For leaf disease classification, the p-value was calculated to be

1.1271e^-37, which is less than the level of significance of 0.05. Thus, the null hypothesis of the study, which is the accuracy of the leaf model not being greater than that of the previous study, is rejected. On the other hand, the p-value of stem disease classification was calculated using the garnered parametric values, amounting to 0.9954e-3. Since the p-value is less than the level of significance, which is 0.05, the null hypothesis of the study, which is the accuracy of the stem model not being greater than that of the previous study, is rejected.

V. Conclusion and Recommendation

A. Conclusion

In this study, a cassava disease detection system using MobileNetV3 algorithm through augmented stem and leaf images was developed where statistical methods were applied to satisfy the objectives of the study, the following conclusions are drawn.

The researchers are able to conclude that the system is significantly capable of detecting disease in the cassava plant through its leaf and stem parts wherein it achieved an accuracy of 93.20% for the leaf and 90.80% for the stem. Therefore, the capability of the system to detect cassava disease was able to exceed the standard accuracy from the previous study of 81.22 % which allows the researchers to recommend the system for effective cassava disease classification.

B. Recommendation

Based on the current study, some recommendations are presented for future studies. Currently, the system is only able to recognize 5 leaf classes and 3 stem classes. Adding more classifications of disease in the system for both leaf and stem parts is recommended to improve the utility of the system, and it is recommended to add the capability to classify the disease of the cassava plant through its tubers, which can be done upon harvest which can contribute to the versatility of the system in utilizing the major parts of the cassava plant in detecting disease. Furthermore, the system only currently uses MobileNetV3, while it is powerful and accurate, the addition of other deep learning algorithms through ensemble stacking should help in increasing the overall accuracy and precision of the system in detecting cassava diseases.

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