RESEARCH ARTICLE

European Journal of Information Technologies and Computer Science
www.ej-compute.org

Tomato Plant Leaf Disease Detection Using Image Recognition: A Case Study of Mlali in Morogoro Region, Tanzania

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ABSTRACT

Tomato plant diseases pose a big problem as they drastically reduce the quantity of a farm's yield and also result in poor tomato quality, which may affect users. Detecting and identifying leaf diseases in tomato plants is a big challenge for farmers and agricultural officers due to the lack of necessary knowledge and diagnosis tools. This study developed a diagnostic tool accessible through a mobile phone application that can easily be used in the field. The tool uses image recognition technology to classify tomato disease from affected plants. The methodology used to develop the image recognition model was a deep learning technique using Convolutional Neural Networks (CNN) architecture, trained and evaluated using four different models for detecting bacterial spots, late blight, early blight, and healthy tomato leaf. Those models were ResNet18, ResNet50, InceptionV3, and EfficientNet. Since the existing dataset was limited, the learning approach was used to transfer knowledge (weight and bias) of selected models and use it to train on the existing data of tomato. The dataset contains 1000 images for each class, but for unknown images only contains 100 images used in training, 50 images for each class used in validation (val), and 50 for each class used in the test. The four classes of common tomato leaf diseases, early blight, late blight, bacterial spots, healthy tomato leaf, and unknown images, were used for training, validation, and testing. The EfficientNet model achieved an F-score accuracy of 0.91%, Resnet50 achieved an F-score accuracy of 0.99%, Resnet18 achieved an F-score accuracy of 0.99%, and InceptionV3 achieved an F-score accuracy of 0.84%. The model evaluation results for all classes were efficient since the confusion matrix gave correct precision, recall, and F-score values for both test and validation datasets. The research picked the resnet18 model for integration with mobile applications because it only uses less memory, and it has given high prediction in the classification of tomato diseases compared to other models. The developed system can detect tomato plant leaf diseases and give farmers procedures on how to control and prevent the disease; also, the system has the benefit of supporting smallholder. Farmers and extension officers detect tomato plant leaf diseases, thus helping to detect diseases at an early stage and helping to increase the quality of tomatoes.

Keywords: Agriculture, Artificial Intelligence, Deep Learning, Machine Learning, Tomato, Transfer Learning.

Published Online: October 03, 2023

ISSN: 2736-5492

DOI :10.24018/ejcompute.2023.3.4.114

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I. Introduction

Agricultural production in sub-Saharan Africa has improved, allowing for economic growth and expansion. Recently, farmers have used modern approaches and technologies to achieve high yields. This study focuses on tomatoes, whereas in Tanzania, most tomatoes are produced by small farmers [1]. Tomatoes provide income and food for these farmers and their communities [2]. Around 70% of the poor live in rural areas, including most tomato farmers. Most tomato cultivation is in regions like Iringa, Morogoro, and Njombe [3].

Tomato is one of the crops affected by pests and diseases, resulting in production losses. The most common pests and diseases affecting tomato crops are early blight, bacterial leaf spot, late blight, bacterial wilt, and septoria leaf spot [4]. Machine learning and deep learning techniques have been used in previous research, especially in the agriculture field, for the detection of various diseases to solve the problem of pests and diseases as the result of better crop quality and also increases disease identification and diagnosis techniques help reduce the risk of destroying ecosystems [5].

Most tomato plants are attacked by viruses, fungi, and bacteria that can appear on the leaves, roots, stems, and the tomato itself, which can cause various effects such as unhealthy plants and stunted growth. Most smallholder farmers use traditional approaches based on laboratory observations, and experiments can lead to incorrect diagnoses the results of laboratory observations take a long time to process due to a lack of control and prevention of disease spread. In addition, the lack of specialized support consultants can make it difficult to identify diseases and pests.

However, most of Tanzania's existing disease detection systems and techniques are physically and manually operated. Others use expensive specialist equipment, such as microscopes. Computer vision systems such as Machine learning and deep learning have not been applied as they need a lot of data for training. This might lead to failure to do well in computer vision systems because of insufficient data training machines. Moreover, this manual method has many limitations, such as expensive processes because many farms are scattered in rural areas, making it difficult for them to reach farmers. This process is also tedious for larger farms and a few agricultural specialists [6].

Therefore, this paper aims to develop a mobile application that facilitates easy detection of Tomato plant leaf disease using image recognition that automates the capture and detection of tomato plant leaf diseases using a mobile phone, reduces the workload on the extension officers in disseminating information to farmers regarding tomato plant leaf disease occurrence.

II. Literature Review

In a study by [7], the authors proposed deep learning for recognizing diseases and pests in tomato plant pictures taken at various camera resolutions. Deep learning model architectures and several CNN object detectors were used. A confusion matrix process, data expansion, and local and global class annotation were used to improve training accuracy and reduce false positives in model evaluation. For end-to-end training and testing, a large-scale tomato disease dataset was used. The algorithm successfully identified nine distinct pests and illnesses of tomato plants from complex settings.

In a study by [8], the authors proposed image processing based on the SVM (Support Vector Machine) algorithm, the method used to detect diseases in tomato plants. The method involves technical analysis of an image where an image is used as the input, and the useful information returns as the output [9]. However, one of the major drawbacks found in the SVM (Support Vector Machine) algorithm is that it can categorize only two (2) inputs, so it was difficult to analyze a large data in the dataset as a result of the system failure and the histogram identical process gives results with poor accuracy.

In research conducted by [10], the authors proposed Machine learning-based recognition algorithms based on two major steps that are feature extraction and classification. The feature from an image was plucked using an appropriate feature extractor. In classification problems, a supervised learning classification algorithm was used mostly. Machine learning techniques are applied in various areas of the agricultural field, like the classification of tomatoes to detect tomato plant diseases using random forest and support vector machine (SVM) algorithms through its leaf images. However, Machine learning techniques have various disadvantages in image classification. One of the major disadvantages is the manual feature extraction process from an image classification using extracted features. So, this problem results in time consumption and tough work. Hence, the concept of deep learning techniques comes into the picture to overcome the above-mentioned issue.

III. Materials and Methods

A. Study Area

This study was conducted in Mlali village in the Morogoro region of Tanzania as shown in the map Fig. 1. Mlali is located in the Morogoro area. Morogoro's capital is around 20 km/12 miles from Mlali (as the crow flies). The geographical location is latitude 7° 5' 51" S, longitude 37° 23' 47" E, and Lat/Long (dec) is -7.0975,37.39659. According to the extension officer, most farmers participate in tomato farming as their main activity, and the tomato growing season is from May to June.

Fig. 1. A map showing Mlali village location in Morogoro region.

B. Methods

Data Collection: To accomplish this study, two methods, a questionnaire and an interview, were used to obtain data that helped develop the system. A questionnaire method was used because it is the easiest way to obtain information quickly in a large population and protects the respondents' privacy. Questionnaires were distributed through different means, including a face-to-face approach, WhatsApp, and email, which were prepared using Swahili. The interview was conducted in the Mlali village in the Morogoro region, which is among the areas in Tanzania that cultivate tomatoes and conducted using formal language (Swahili). The interview was conducted to collect data on the common tomato leaf diseases that affect them most and to know each disease in depth. Another interview was conducted with Sokoine University of Agriculture students who are in the agriculture field working as extension support officers in the pests and diseases management on crops; the reason for doing the interview was to get information on the most common tomato leaf diseases, obtained insights about those diseases and how to control them.

Sample and Sampling Technique: The sampling technique used in selecting the sample was snowball sampling. Snowball sampling is a technique in which you interview anyone you meet, and that individual leads you to another person who corresponds to your study until you have a sufficient number of people. This approach is most applicable in small populations that are difficult to access due to their inaccessible professions [11]. This sampling technique was used because it is not easy to recognize farmers and extension support officers engaged in tomato farming. The total number of people (sample) from whom data was collected was 30 farmers and 15 extension support officers; from this total, there were 10 farmers, 13, and 5 extension officers interviewed. Therefore, the total number of people interviewed was 15, and the number of people who responded to the questionnaire was 45.

C. Data Analysis

Data collected from questionnaires were analyzed using analytics available in Google Forms. In data analysis, data of farmers and extension support officers were analyzed separately. Also, Data collected from interview sessions were farmers and extension support officers did the interview, and answers (data) were collected separately.

D. Analysis of Results

More than 60 respondents were obtained from people who were engaged in tomato farming or had heard about tomato farming and extension support officers, who were interviewed and given questionnaires since both are users of the system. The following is the summary of the questions asked to farmers and extension support officers:

1) Farmer's awareness about tomato plant leaf diseases

This question asked whether the farmers/extension supports knew of tomato plant leaf diseases. 96.4% of farmers said yes, they know about tomato plant leaf diseases, and 3.6% of farmers said no, they did not know about tomato plant leaf diseases. Fig.2 shows the farmer's/extension awareness about tomato plant leaf diseases.

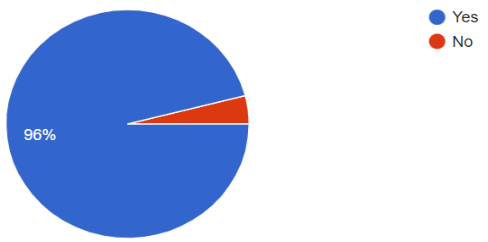

Fig. 2. Farmers'/Extension Support awareness of tomato plant leaf diseases.

2) Most common tomato plant leaf diseases that affect farmers in their areas

This question aimed to know the most common tomato plant leaf diseases that affect farmers in their areas. Through the questionnaire obtained, the most common tomato plant leaf diseases that affect tomato agriculture in different areas were ugonjwa wa Kutu (Bacterial spots), bakijani tangulia (Early Blight), and bakijani chelewa (Late Blight), and Mnyauko (Bacterial wilt). Fig.3 shows the common tomato plant diseases.

3) Main causes of tomato plant leaf diseases

This question aimed to know the most common causes of tomato plant leaf diseases that affect tomato agriculture in their areas. It seems that most causes of the diseases were caused by a lack of knowledge among farmers about the disease's detection skills and weather conditions. Fig. 4. summarizes the causes of tomato plant leaf diseases.

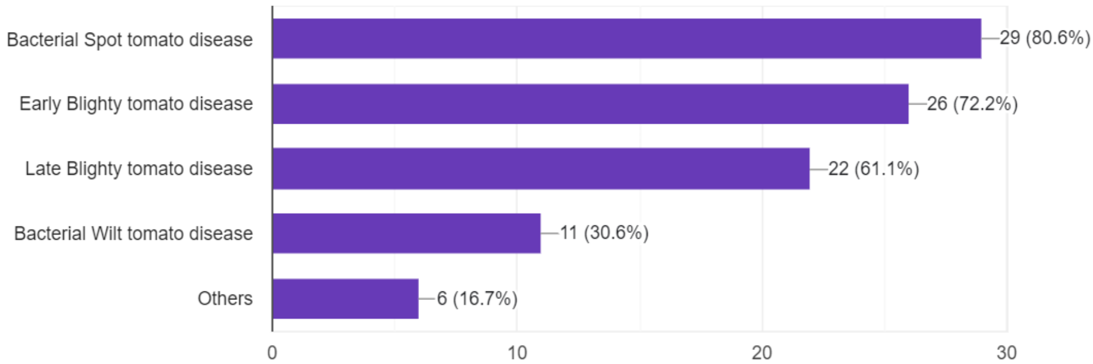

Fig. 3. Common tomato plant leaf diseases occurred.

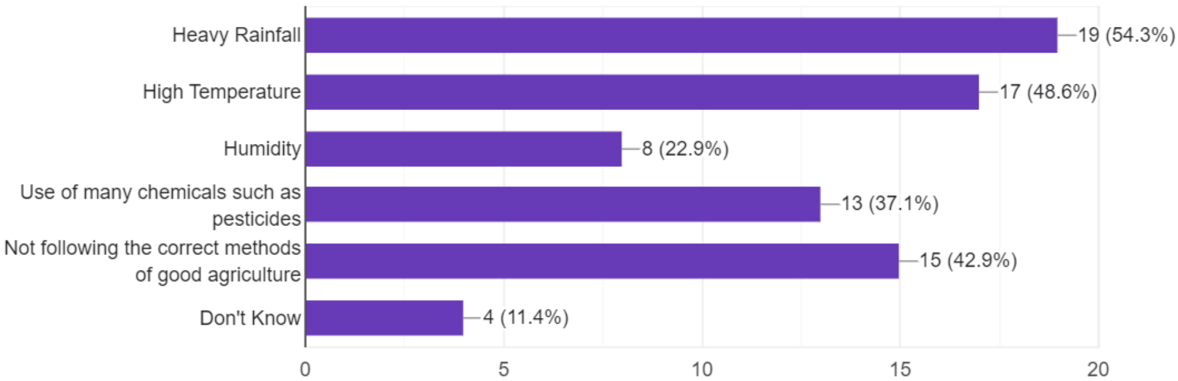

Fig. 4. Causes of tomato plant leaf diseases occurred.

IV. Interpretative Oversight in Machine Learning

Deep learning methods like convolutional neural networks deal with unstructured things like images and sounds. Therefore, deep learning methods and advances in computer vision make it possible to improve crop protection against plant diseases in the agricultural sector [12]. According to [13], the authors explained that CNNs were trained on the detection of tomato plant leaf diseases such as bacteria wilt, early blight, and bacterial spot of 1000 images of the dataset and achieved an accuracy of 92.3%, while after 100 epochs the training accuracy was 95.8%. The CNN's methodology was used to allow for easy and fast system implementation during training. The CNN architecture model trained the datasets to distinguish between healthy and unhealthy leaves, and the final results were 95% accurate.

According to [14], the authors explained the Convolution Neural Networks (CNNs) method to identify and detect tomato leaf plant diseases from different plants by using leaves images. A CNN consists of a four-layer convolution layer where the image (original image) is filtered to perform the convolution operation, a ReLU layer, which is used to reduce the exponential growth in the calculation needed to function the neural network, a pooling layer, which used to reduce image dimension, and a fully connected layer. They used different detectors for disease detection and classification using an architecture called Region-based Fully Convolutional Network. The CNN architecture was tested with datasets from images downloaded from the internet and captured using camera devices from different places.

V. Role of Machine Learning in Agriculture

Machine learning involves the ability of a computer to train, analyze, and identify data to perform a certain task without human intervention [15]. Machine learning consists of deep, supervised, and unsupervised learning, which contributes greatly to agriculture development. Machine learning technologies are important in the agriculture sector because they help in disease detection, proper production, soil management, crop recognition, and water management as a result of the improvement of crop production, reducing cost, efficiency to reduce environmental pollution, minimal resources usage, fewer labor expenses, and time-consuming [16].

VI. Tomato Sub-system (Model) Development

A. Dataset

The dataset used to train, validate, and test the tomato sub-system was obtained from the Kaggle data science company; the dataset was obtained through the URL https://www.kaggle.com/kaustubhb999/tomatoleaf. The dataset contains 1000 images for each class in train and 50 images for each class in validation (val) and 50 images for each class in the test. The five classes of common tomato leaf diseases, early blight, late blight, bacterial spots, unknown image, and healthy tomato leaf were used for training, validation, and testing.

PyTorch library was used as a baseline during implementation on the backend to enable models to have high performance for numerical computation during training. The software library used to train the selected models was the Google Collab machine with runtime type as Python3, Notebook size of 20Mb, and hardware accelerator as GPU.

B. Data Preparation

Before training the obtained datasets, the first thing to do was to prepare the existing datasets in a form that can be easy to train, validate, and test to produce the best accuracy for the prediction process. The followings are the procedures and steps used in the data preparation process as follows:

1. Convert obtained datasets to tensor; for the model/computer to understand images, they must be represented in pixels and collected weather in an array or tensor. The obtained datasets were corrected from pixels into tensors to make it easy for them to pass through GPUs during training to speed up the training process.
2. Data augmentation is the process of increasing image data size by transforming existing images through flip, rotation, crop, and image resize. Getting enough datasets is challenging and financially costly to generalize the knowledge for a particular problem. So, to get enough datasets, we have to use the datasets we already have to generate even more datasets for our model to train. This technique helps to get the best accuracy.
3. Data normalization: The process helped train data faster, and parameters converged toward the minimum optimum. So, for the obtained data, normalization was applied to the pixel values of the images. Basically, normalization was done by calculating the mean and standard deviation of the existing images, considering which size to use, minimizing the mean from images to get zero mean, and then dividing the existing images with standard deviation to round all pixels in images from 0 to 1. This helped the model converge faster toward the optimum position during training. The input image was normalized using with standard deviation = [0:229; 0:224; 0:225] and mean = [0:485; 0:456; 0:406].

C. Transfer Learning Selected Models

The transfer learning technique takes a model trained on a large dataset and transfers its knowledge to a smaller dataset for increased learning in the target task by using information from the source task features linked to the task-specific dataset's target class [17]. Four pre-trained (reused) models such as ResNet18, ResNet50, InceptionV3, and EfficientNet, were used with transfer learning to transfer knowledge (weight and bias) of selected models and use it to train existing data of tomatoes convolutional neural networks and assess the applicability of these techniques for the classification problem described in this research dissertation. The selected four models are among the CNN model architecture and are the foremost state-of-the-art in computer vision tasks. Fig. 5 shows the convolution neural network architecture.

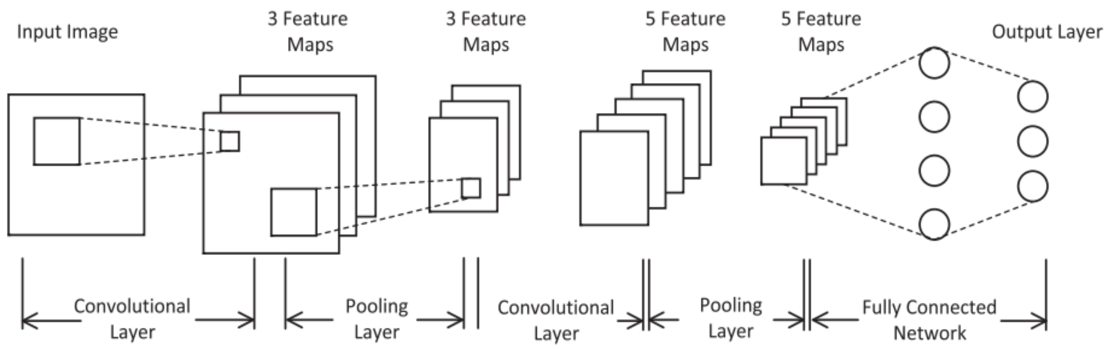

Fig. 5. Convolutional Neural Networks (CNNs) architecture for tomato plant disease detection.

D. Model Training and Results

1) Residual Network Models

Resnet models were designed to enhance true positives while decreasing false negatives. Cross-entropy loss was employed as the goal function, and its value increases as the anticipated probability deviates from the true label. Resnet18 is a convolutional neural network that is 18 layers deep, and Resnet50 is a convolutional neural network that is 50 layers deep. The hyper-parameters used to train the Resnet models were the number of epochs used was 25, the optimizer was SGD (Stochastic Gradient Descent), the image size was 224×224 pixels, momentum was 0.9, the learning rate was 0.001, which decreases every seven epochs by the factor of 0.1 for all 25 epochs and batch size was five used during training. The accuracy obtained after training and then validation accuracy for Resnet18 was 0.990000 (99.00%), and for Resnet50 was 0.990500 (99.05%). Fig. 6 shows the model accuracy results for Resnet18.

During the training process of the Resnet18 model for 25 epochs, the last 24 epochs produced a training loss of 0.1294 with an accuracy of 0.9653 for training and validation; the loss was 0.0265 with an accuracy of 0.9900. Therefore, the training was completed in 34 minutes and 47 seconds, and the best validation accuracy was 0.997500 (99.75%).

Again, during the training process of the Resnet50 model for 25 epochs, the last 24 epochs produced a training loss of 0.691 with an accuracy of 0.9810 for training, and for validation, the loss was 0.0243 with an accuracy of 0.990. Therefore, the training was completed in 34 minutes and 7 seconds, and the best validation accuracy was 0.995000 (99.50%). Fig. 7 shows the training and validation of the model accuracy results for Resnet50.

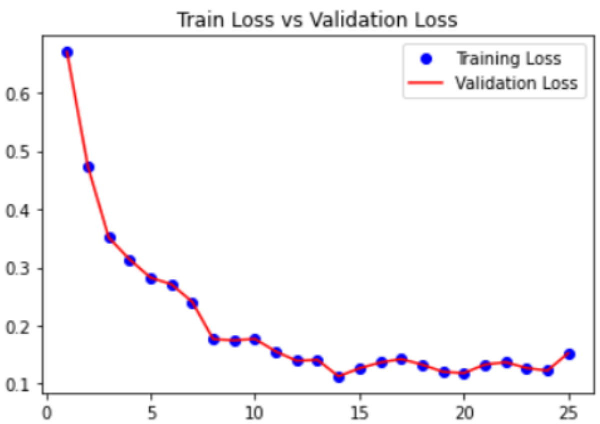

Fig. 6. Model accuracy results for Resnet18.

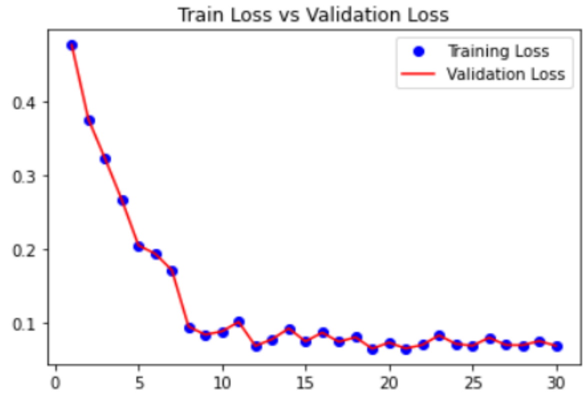

Fig. 7. Model accuracy results for Resnet50.

2) InceptionV3 Model

The hyper-parameters used to train the InceptionV3 model were the number of epochs used was 20, the optimizer was SGD (Stochastic Gradient Descent), the image size was 299×299 pixels, momentum was 0.9, the learning rate was 0.001, which decreases every seven epochs by the factor of 0.1 for all 20 epochs and batch size was five used during training. The accuracy obtained after training and validation for the InceptionV3 model was 0.84500 (84.50%). Fig. 8 shows the inceptionV3 model accuracy results. The hyperparameters were used in the training process of the InceptionV3 model, but for the Learning, the rate decreases every seven epochs by a factor of 0.1 for all 20 epochs.

After the training process of the InceptionV3 model for 20 epochs, the last 19 epochs produced a training loss of 0.9887 with an accuracy of 0.7045 for training, and for validation, the loss was 0.3968 with an accuracy of 0.8150. Therefore, the training was completed in 21 minutes and 12 seconds, and the best validation accuracy was 0.885000 (88.50%).

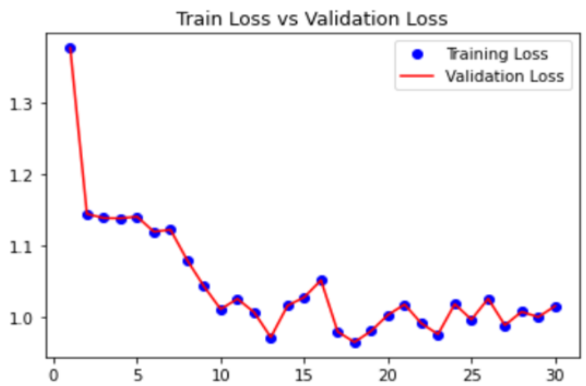

Fig. 8. Model accuracy results for InceptionV3.

3) *EfficientNet Model*

The hyper-parameters used to train the EfficientNet b0 model were the number of epochs used was 20, the optimizer was SGD (Stochastic Gradient Descent), the image size was 224×224 pixels, momentum was 0.9, the learning rate was 0.001 which decreases every seven epochs by the factor of 0.1 for all 20 epochs and batch size was five used during training. The accuracy obtained after training and validation for the InceptionV3 model was 0.84500 (84.50%). Fig. 9 shows the EfficientNet model accuracy results. The hyperparameters were used in the training process of the InceptionV3 model, but for the Learning, the rate decreases every seven epochs by a factor of 0.1 for all 20 epochs. After the training process of the EfficientNet b0 model for 20 epochs, the last 19 epochs produced a training loss of 0.9889 with an accuracy of 0.8045 for training. For validation, the loss was 0.4968 with an accuracy of 0.8350. Therefore, the training was completed in 25 minutes and 1 second, and the best validation accuracy was 0.880500 (88.05%).

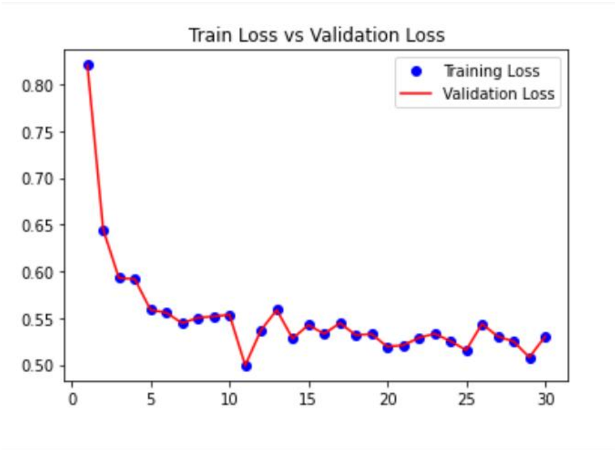

Fig. 9. Model accuracy results for EfficientNet.

E. *Model Evaluation*

1) *Models Testing Classification Results*

All four models were selected for testing after training and validation processes finished each model, such as Resnet18, Resnet50, InceptionV3, and EfficientNet, done testing with the test images. Results for the testing for each model were successful since each model gives the correct output of the selected image with the corresponding class indexes loaded from the test images and predicted with the test class images where the class with high probability will be predicted value. Fig. 10 shows the test classification results for the Resnet18 model. The following was testing confusion matrix results for the Resnet18 model regarding f-score, recall, accuracy, and precision.

1) *Confusion Matrix Results*

The confusion matrix (CM) is a table used to visualize classifier performance using the data in the matrix. A confusion matrix was created for the test set with 50 images for bacterial spot, 50 for early blight, 50 for late blight, 50 for healthy, and 50 for unknown.

Confusion matrix results for the Resnet18 model show that the model succeeded in detecting diseases of the class from test data with great accuracy presented in Fig. 11, while on the validation set, the model confused with only a few images between tomato bacterial spot and tomato late blight shown in Fig. 12.

	precision	recall	f1-score	support
0	1.00	1.00	1.00	50
1	1.00	1.00	1.00	50
2	0.93	1.00	0.96	50
3	1.00	0.92	0.96	50
4	1.00	1.00	1.00	50
accuracy			0.98	250
macro avg	0.99	0.98	0.98	250
weighted avg	0.99	0.98	0.98	250

	precision	recall	f1-score	support
0	1.00	1.00	1.00	50
1	1.00	1.00	1.00	50
2	0.93	1.00	0.96	50
3	1.00	0.92	0.96	50
4	1.00	1.00	1.00	50
accuracy			0.98	250
macro avg	0.99	0.98	0.98	250
weighted avg	0.99	0.98	0.98	250

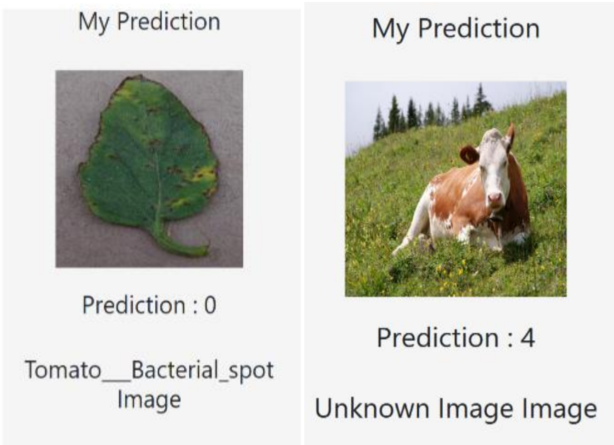

Fig. 10. Resnet18 model testing classification result.

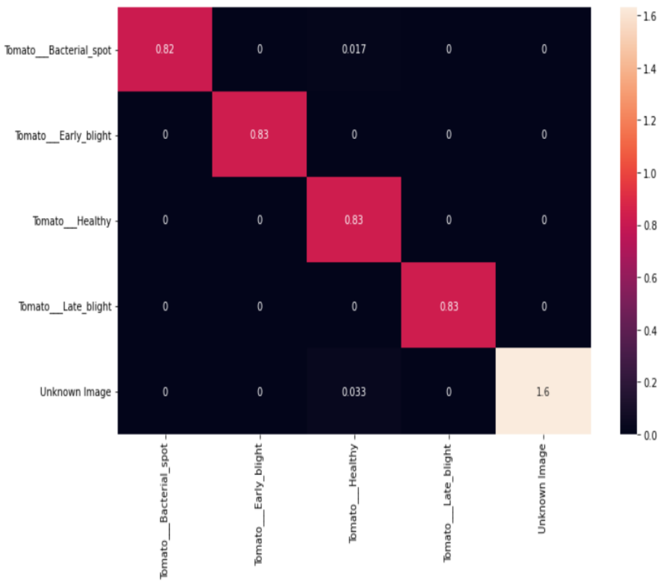

Fig. 11. Test Confusion Matrix for Resnet18 Model.

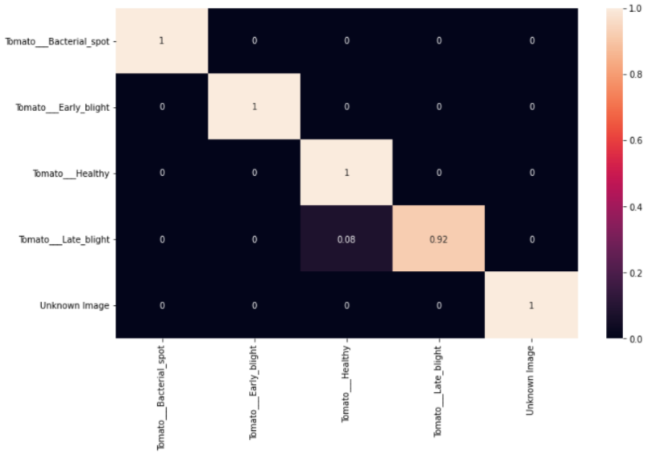

Fig. 12. Validation Confusion Matrix for Resnet18 Model.

The confusion matrix plot result for the Resnet50 model shows that the model succeeded in detecting diseases of the class from test data with great accuracy, as exhibited in Fig. 13, while on the validation set, the model was confused with only a few images between tomato bacterial spot and tomato late blight shown on Fig.14. The confusion matrix for the Resnet50 model in the test dataset and validation dataset.

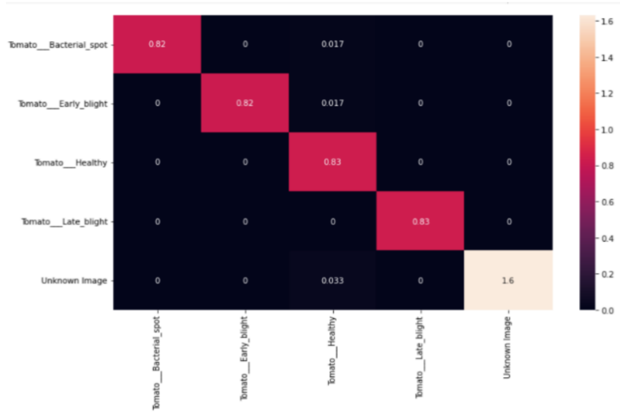

Fig. 13. Test Confusion Matrix for Resnet50 Model.

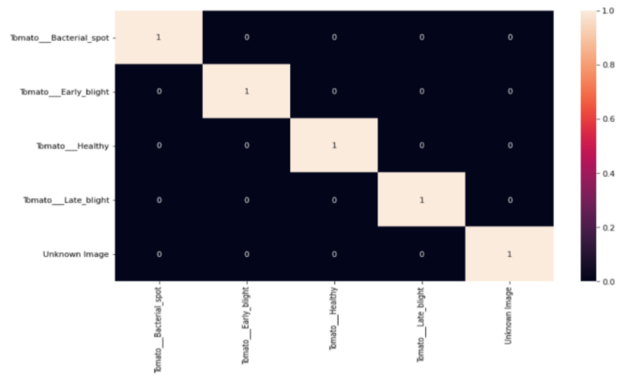

Fig. 14. Validation Confusion Matrix for Resnet50 Model.

The confusion matrix plot result for the EfficientNet model shows that the model succeeded in detecting diseases of the class from test data with great accuracy. At the same time, on the validation set, the model is confused with only a few images between tomato bacterial spots and tomato late blight. The test result is shown in Fig. 15 for the EfficientNet model. On the other hand, Fig. 16 shows the validation of the confusion matrix for EfficientNet model.

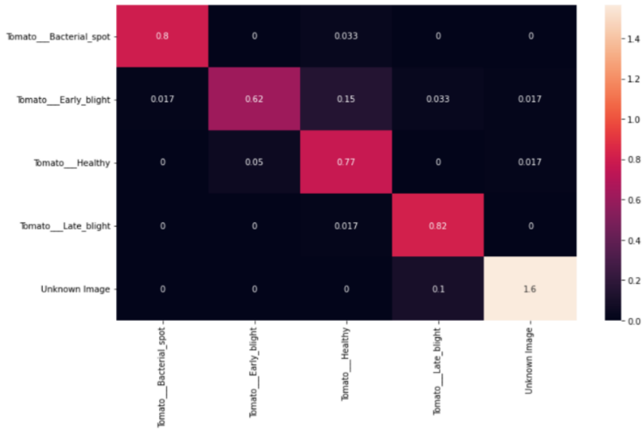

Fig. 15. Test Confusion Matrix for EfficientNet Model.

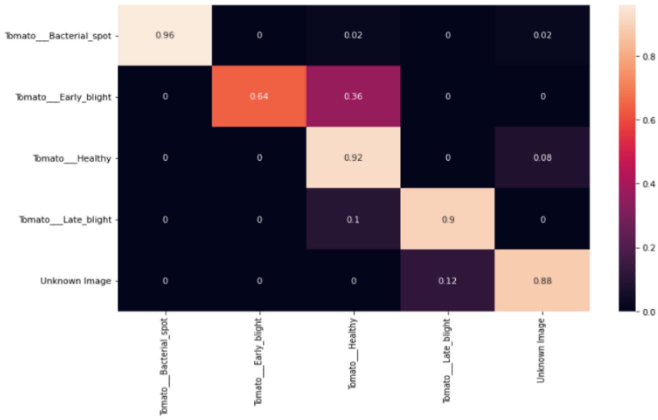

Fig. 16. Validation Confusion Matrix for EfficientNet Model.

The confusion matrix plot result in the InceptionV3 model shows that the model succeeded in detecting diseases of the class from test data with great accuracy. At the same time, on the validation set, the model was confused in some classes. The result of the test confusion matrix is shown in Fig. 17. Moreover, the validation of the dataset for the confusion matrix of the InceptionV3 model is presented in Fig. 18.

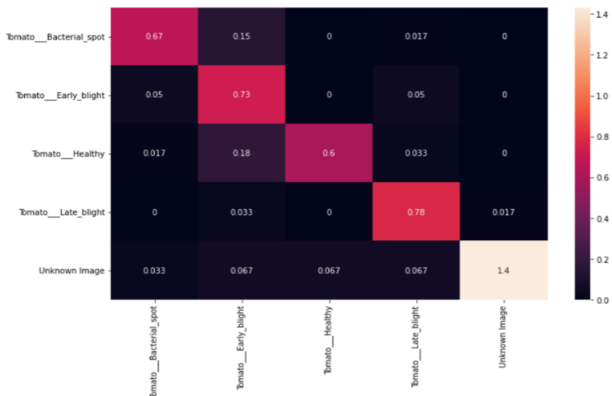

Fig. 17. Test Confusion Matrix for InceptionV3 Model.

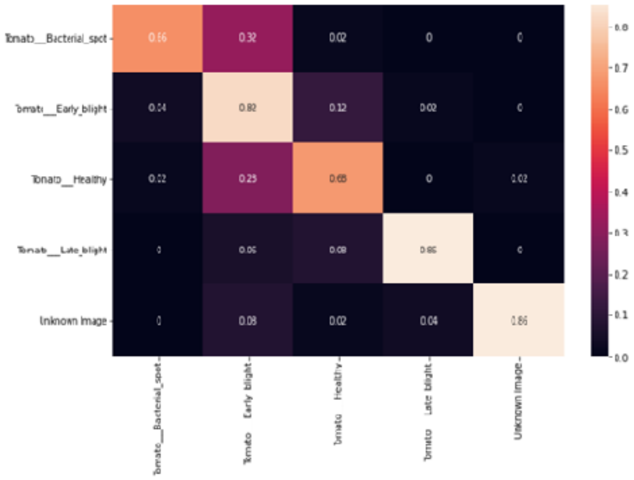

Fig. 18. Validation Confusion Matrix for InceptionV3 Model

F. Integration of Mobile Application and model (Tomato Subsystem)

The mobile app and mobile integration were done through API (Application Programming Interface), where the model and app work independently and communicate via API. When the user captures or uploads a tomato plant leaf image, the image is uploaded, sent to the model web service through API, translated by the model, and sent the result again through API to a mobile application where the user can see the result of the uploaded image. The model serves, database, and web should be active in order to allow the image processing in the mobile application and the user to see the result that the model (tomato subsystem) predicts.

VII. Conclusion

Agriculture, like any other sector, has received numerous digital transformations brought by emerging technologies aimed to help farmers increase productivity and produce secure food to be consumed by society. The current study aimed to develop a mobile application to aid in detecting tomato plant leaf disease using image recognition. A deep learning technique using Convolutional Neural Networks (CNN) was used to train the model to help make proper decisions once the tomato leaf disease is detected. It is recommended that further research be undertaken on other food crops to help farmers and extension officers in agricultural activities.

Acknowledgment

We wish to thank all who contributed to the successful implementation of this project.

Conflict of Interest

The authors declare that they do not have any conflict of interest.

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