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Banana Leaf Disease Classification Using SqueezeNet, AlexNet and MobileNet

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Abstract

Banana production is a vital component of global agriculture, facing significant challenges due to various leaf diseases. These diseases can cause substantial yield losses, impacting both farmer livelihoods and industry development. Early and accurate disease detection is crucial for implementing effective management strategies. This study explores the application of Convolutional Neural Network (CNN) for banana leaf disease classification. Three pre-trained CNN architectures, SqueezeNet, AlexNet, and MobileNet, were evaluated for their ability to distinguish between Black Sigatoka, Fusarium Wilt, and healthy banana leaves. A comprehensive dataset containing 3000 images per class was employed for training and testing, with an 8:1:1 train-validation-test split. Performance evaluation metrics included accuracy and loss rate. Among the evaluated models, MobileNet achieved the highest accuracy (94.89%) and the lowest loss (0.1484), demonstrating its effectiveness in banana leaf disease detection. These findings suggest the potential of CNNs as a valuable tool for precision agriculture applications.

1. Introduction

Nowadays, crop diseases have become a massive concern to farmers due to the losses in the yield of agricultural products from the diseases [1]. Moreover, the quality of the agricultural products is also seriously affected by the diseases in the production process. Furthermore, there are various diseases that are very hard to control, which will lead to crop epidemics where crops must be destroyed, and the land can't be used for planting for a period of time [2]. Ultimately, it will lead to substantial economic losses for the farmers and cause agricultural product shortages. Hence, it is crucial to prevent the disease through detection at an early stage to reduce the loss.

Among the crop diseases, the banana plant disease has grown to be a major concern for the farmers, who need to sustain the quality of the bananas. If the disease isn't found in the early stage of the plantation, it may lead to a banana epidemic on the farm, and it can reduce the production and quality of bananas. The current method for detecting banana disease relies on farmers' observations of the banana leaves, but this can lead to misinterpretation of the disease [3] - [6].

2. Literature Review

2.1 Banana Leaf Disease

Bananas are one of the most important fruits and one of the most popular tropical fruits in the world due to their high nutritional content and low cost. After cereals, sugar, coffee, and cocoa, bananas are the fifth most traded agricultural product worldwide, with over 100 billion consumed each year. However, banana production has declined sharply in the last few years, with about 50% yield loss due to diseases [3] - [9].

For every type of plant, there are three types of disease which are bacterial, viral and fungal. Therefore, the banana plant also has bacterial, viral and fungal diseases. Among these three diseases, the most common banana plant diseases are Black Sigatoka, Cordana spot, and banana leaf speckle [9].

Currently, the methods to detect banana plant diseases are the same as those of crop disease detection, which are manual detection by experienced farmers and automatic detection by using image processing algorithms. The diseases can be detected only on the leaves or stems of the banana plant [7], [8].

The manual detection method requires experienced farmers to detect banana plant diseases as they know how to distinguish them based on the visual patterns and the color of the leaves and stems of the plant. Some banana plant diseases have similar symptoms, so amateur farmers might be unable to distinguish them [3] - [8].

2.2 Convolution Neural Network (CNN) Algorithm

Among the models in Convolutional Neural Networks (CNN), there is a model called SqueezeNet, a lightweight CNN model that works well on image classification tasks and is accurate. SqueezeNet has only 800,000 parameters compared to other models with more parameters and has an accuracy rate comparable with the other models [10] - [12]. SqueezeNet, AlexNet, and MobileNet were used in this project to compare and obtain the best CNN algorithms. SqueezeNet is used because it is a simple and effective lightweight CNN architecture with acceptable performance in feature extraction. This model consists of 14 layers only. Then, AlexNet is used because it is a simple CNN architecture with only 8 layers that have decent performance in feature extraction, whereas MobileNet is used because it is an effective CNN architecture with 28 layers and has an acceptable performance in feature extraction.

To ensure that the network has a large activation map, SqueezeNet substitutes the 1x1 convolution core for the 3x3 convolution core, decreases the number of input channels for the 3x3 convolution core, and delays the down-sampling as shown in Fig. 1[10]. With the restricted number of parameters, these techniques were used to lower the parameters and increase the accuracy [10].

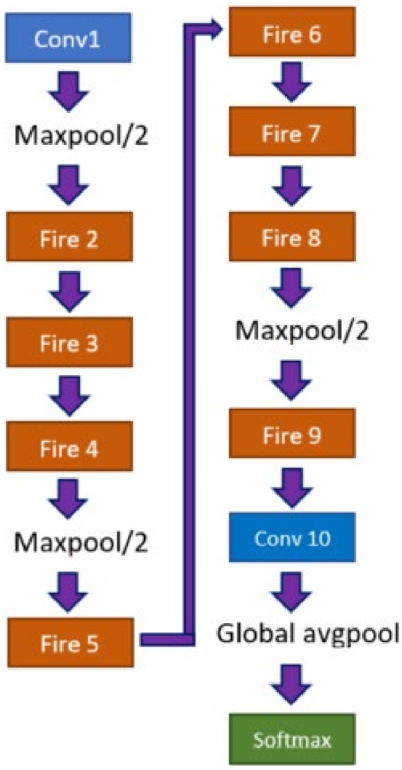


Fig. 1 *Flowchart of the SqueezeNet [10]*

The main structure of the SqueezeNet algorithm is the Fire Module. In the SqueezeNet algorithm, the Fire Module is used to replace general convolution layers and pooling layers. In the structure of the Fire Module in the SqueezeNet algorithm, the Fire Module consists of both Squeeze and Expand functions, in which the Squeeze function is a convolution layer with a 1x1 convolution core and the Expand function is composed of 1x1 and 3x3 convolution layers. In the structure of SqueezeNet, SqueezeNet only consists of Fire Modules, pooling layers, and .1 final loss layer, which helps in reducing the model size and compromising the detection accuracy of the system [10].

Other than SqueezeNet, AlexNet is also one of the Convolutional Neural Network (CNN) image processing algorithms. The AlexNet algorithm is the first deep CNN architecture, which was proposed in 2012. In image recognition and classification tasks, AlexNet demonstrated groundbreaking performance even though it was the first deep CNN design [13].

In the structure of AlexNet algorithm, it consists of five 2D convolutional layers (Conv2D) and three fully connected layers (FC) as shown in Fig. 2. Every convolutional layer contains a set of convolutional kernels that function as filters. The kernel is an integer matrix that multiplies its weights by corresponding values from a subnet of the input image. After that, the chosen subnet of the input image's pixels will contain a similar dimension to the kernel, where the values obtained from the process are summed up to produce one value that represents each pixel's value in the output. In summary, the convolutional layer's output is produced in both dimensions (height and width) by the kernel as it moves across the input image [13].

After the convolutional layer, the pooling layers will sum up the identical information in the local region generated by the convolutional layer and produce an output of a single value within that region. Before the next convolutional layer, the batch normalization function is used to prevent overfitting. After the feature extraction phase, three fully connected layers are used to perform classification globally, followed by a dropout layer, which is used to randomly skip some units and connections with a certain probability within the network. Finally, the structure of AlexNet ends with an output layer [13].

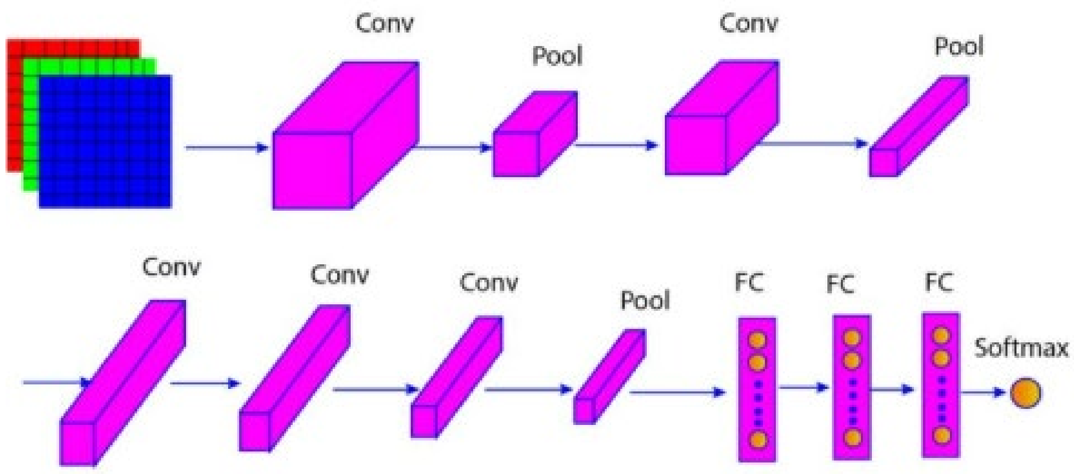


Fig. 2 *Flowchart of the AlexNet [13]*

Other than SqueezeNet and AlexNet, MobileNet is also one of the Convolutional Neural Network (CNN) image processing algorithms. Among the CNN algorithms mentioned, the MobileNet algorithm is an efficient and lightweight model that consists of a smaller number of parameters. In the first few layers of the MobileNet algorithm, it uses depthwise separable convolutions to decrease the computational task, which results in lighter weight [14].

In the structure of the MobileNet algorithm, it consists of two different kinds of core layers, which are depth wise convolutions and pointwise convolutions shown in Fig 3. The depth wise convolutions are used to filter the input without creating new features, whereas the pointwise convolutions are the function to create new features. Hence, the depth wise separable convolutions are the combination of both functions. Each depth wise separable convolution layer started with the depth wise convolution layer and was followed by the batch normalisation layer and ReLU activation layer. After ReLU activation, pointwise convolution layer is used to create the new features and followed by normalisation layer and ReLU activation [14].

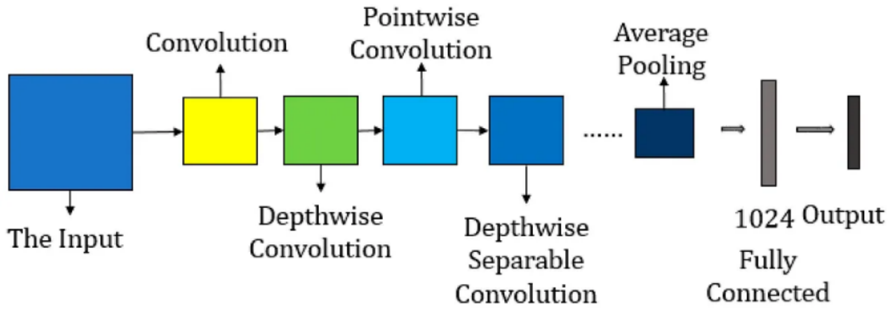


Fig. 3 *Flowchart of the MobileNet [13]*

After the depthwise separable convolutional layer, the global average pooling layer will sum up the identical information in the local region generated by the convolutional layers and produce an output of a single value within that region. Then, the reshape layer and dropout are used to prevent overfitting. After that, a convolutional layer is used followed by a softmax activation layer and reshape layer.

2.3 Previous Research About Banana Disease Detection Using Image Processing

In a study by [5], a method for detecting banana leaf disease images with intricate backgrounds was developed by combining color segmentation, the Ostu method and histogram threshold segmentation. The study focused on the intricate image components seen in the image of the banana leaf disease that was formed from the natural environment. Green elements, such as healthy leaves and green weeds, and non-green objects, such as disease spots, soil, and dead leaves, are intricate image features that will affect the disease detection results. The process of disease detection is segmenting the banana leaf disease image by color, segmenting the healthy leaves and weeds, removing the non-green background, such as soil and dead grass, using the Ostu segmentation, and finally, eliminating the background noises using the area threshold method, and thus extracting a complete disease spot target. Hence, the study's average segmentation accuracy rate and error rate were 97% and 2.3%, respectively. These results suggest that the method can accurately segment the disease spot areas of banana leaf disease images with complex backgrounds and provide a solid foundation for feature extraction and banana leaf disease recognition later.

Another research by [9] used image pre-processing, image segmentation, feature extraction using CNN and image classification using SVM to detect banana leaf diseases such as Black Sigatoka, Cordana leaf spot and banana leaf speckle. Image pre-processing technique was used to reduce noise, resize, improve image quality and decrease flickering in the banana leaf disease images, followed by extracting the features through three convolution layers and subsequent pooling layers. After that, the characteristic of the banana leaves obtained previously is then classified at the fully connected layer (SVM). Hence, the study concluded that the average results of using CNN and SVM algorithms have 94% accuracy in detecting 3 banana leaf diseases.

A banana leaf disease identifier algorithm was recently researched by [4], which proposed using stitching, equalization, image segmentation, feature extraction, and classification using SVM. In image pre-processing, two images are taken of each leaf, stitched together, and equalized to correct contrast. Following the pre-processing stage, each image's key features are extracted using the SIFT algorithm, and feature matching is performed using the BruteForce (BF) Matcher. By applying the "AND" function to the original image, Otsu Thresholding removes the background and produces an image with the banana leaf already segmented, which is needed to extract the Region of Interest (ROI). Then, feature extraction is done using Color Detection with HSV color space. Hence, the brown spots found on the banana leaf are the key feature of Sigatoka disease. Therefore, the study conducted with the average results of using the SVM algorithm has 90% accuracy in detecting Sigatoka spot disease on banana leaves.

According to research by [8] using feature extraction and K-means clustering techniques to detect banana leaf diseases such as Panama disease, Bacterial Wilt, CMV and Sigatoka. To obtain proper results, the process began with pre-processing the images by resizing the images into a standard size and removing the noise. Following that, the contrast of the images is enhanced and RGB images are converted into L*a*b* so they can be readily segmented from L*a*b* color space. After that, the disease region is identified by segmenting the images using the K-means clustering technique. The K-means algorithm finds a partition in which similar object clusters are closer to one and farther from objects in other clusters. The process is followed by feature extraction based on the color, shape and texture. Finally, the Support Vector Machine (SVM) is used to classify diseases. To recognize diseases, it uses the linear kernel function. Following the study's completion, an average result with an accuracy of 85% was obtained for the detection of four different diseases, which are Sigatoka disease, Cucumber Mosaic Virus, Bacterial Wilt and Panama disease.

Lastly, research from [7] recommended employing the histogram-based equalization and Fuzzy c-means clustering method to detect banana leaf diseases such as Black Sigatoka, Freckle disease, and Anthracnose disease [7]. The first steps in the pre-processing stage include cropping, resizing, filtering and color conversion. To obtain a uniform-dimensional image for efficient processing, scaling is necessary. The filter is then used to eliminate unwanted regions from the banana leaf because it contains more dust particles and dew droplets on it. The Gaussian filters are used to eliminate the noise from the region. Therefore, as the Gaussian filter converts the colored image into a greyscale image, histogram-based equalization is used to enhance the intensity and contrast of the image. Subsequently, the images undergo segmentation, which involves splitting the image into multiple segments and separating the region of interest (ROI) from unwanted regions. The images in this study are segmented using the Fuzzy c-means clustering technique. This technique segments the provided leaf set into cluster form, which represents subsets and groups. After that, the image's feature is extracted and classified according to the diseased part of the banana leaf. The feature extraction classification is based on pattern recognition to identify the type of disease. After the feature has been extracted, the ANN toolbox uses it as input to detect and classify banana leaf diseases. In conclusion, it demonstrated a high degree of accuracy in detecting four distinct types of diseases, which are Sigatoka disease and freckle leaf disease.

3. Methodology

Fig. 4 shows a flowchart of the project on developing a banana leaf disease detection in Jupyter Notebook. The process started with acquiring image datasets that contained images of healthy banana leaf and banana leaf with Black Sigatoka and Fusarium Wilt from the Harvard Dataverse website. The dataset was split into 3 sets, which are the training set, validation set and testing set. The dataset was split into 8:1:1 dataset ratio.

After splitting the datasets, the training set and validation set were pre-processed and used to train under three different CNN algorithms, which are SqueezeNet, AlexNet, and MobileNet. For this phase, the aim was to achieve an accuracy of 80% and a loss value of less than 1 [8], [9]. If the trained model did not achieve the following conditions, the model was repeatedly trained with a bigger epoch until the conditions were fulfilled.

After training, the CNN models were tested and evaluated based on their performance metrics. With the help of classification reports of every CNN model, the CNN models were compared based on their performance and the best CNN model was found.

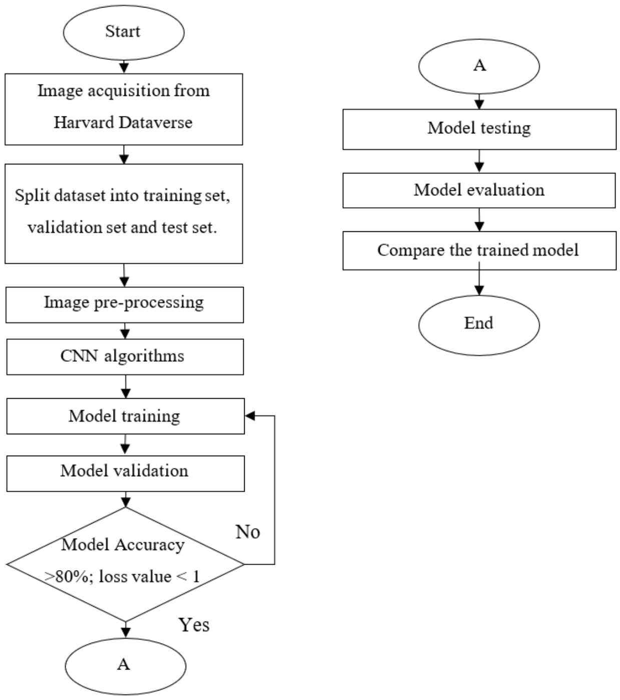


Fig. 4 *Flowchart of the SqueezeNet, AlexNet and MobileNet (CNN) model development*

The dataset consists of 9000 images, which consist of healthy banana leaf, banana leaf with Black Sigatoka and banana leaf with Fusarium Wilt. The dataset was split into three sets, which are the training set, the validation set and the test set, in an 8:1:1 dataset ratio. Table 1 shows the overview of the splitting of the dataset obtained from the Harvard Dataverse, and Fig 5 shows some of the sample images used.

After pre-processing, the process goes through convolutions process block elements with different rescaling and resampling operations. A total of three features are extracted and saved into a separate database for future use. After extracting the features from the banana leaf images, the features are classified based on the disease of the banana leaf image. In this phase, the CNN models use a final set of layers that produce class probabilities. Finally, the banana leaf diseases are classified into three classes: Healthy, Black Sigatoka and Fusarium Wilt.

Table 1 *Overview of the dataset*

Classes	Images for training	Images for validation	Images for testing	Total images
Healthy	2400	300	300	3000
Fusarium Wilt	2400	300	300	3000
Black Sitoga	2400	300	300	3000


(a) **(b)** **(c)**

Fig. 5 *Image sample of banana leaf with (a) Healthy; (b) Black Sigatoka; and (c) Fusarium Wilt*

Image resizing and interpolation techniques are then used to pre-process the images. This is because the images acquired might have different dimensions and might be too large for training, which results in longer training time. Therefore, resizing modifies the image's dimensions to a specific dimension, whereas interpolation modifies the pixels of the images after resizing to keep the details of the full images. This stage standardizes the picture measurements and reduces unwanted components. Besides, this improves the compatibility with other processing processes and the efficiency of the processes. In this study, the training dataset was resized into dimensions of 224x224 pixels using the TensorFlow Keras utility library. The resizing and interpolation process happens during the dataset creation process.

Finally, the SqueezeNet, AlexNet and MobileNet are used to perform feature extraction and classification tasks. The feature extraction technique reduces the number of features in a dataset by creating new features from the present one.

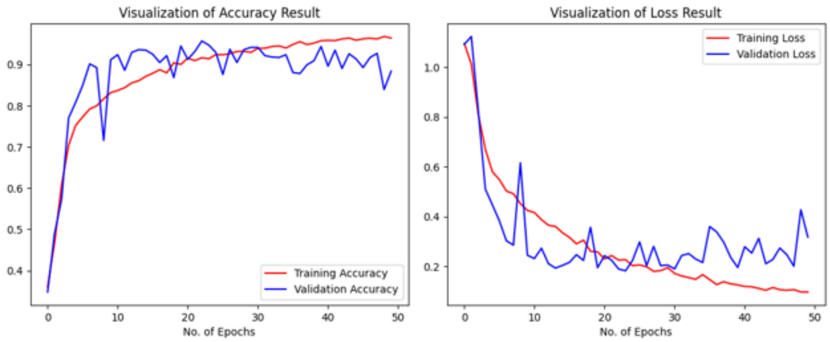
4. Result

In the training phase, the SqueezeNet, AlexNet and MobileNet models were trained using 3000 datasets per class with 8:1:1 dataset ratio of training, validation, and testing. The batch size used is 16 with learning rate of 0.0001 to provide an accurate estimation of gradient and escape sharp local more easily. All the training was done offline using a personal laptop with Intel Core i5-8265U CPU 1.6 GHz and 12 GB 2400 MHz RAM.

4.1 Performance of SqueezeNet Algorithm Model

Fig. 6, which shows accuracy on the left and loss on the right during a 50-epoch period, demonstrates the SqueezeNet model's performance. The model successfully learns from the training data when the training accuracy rises gradually and settles at around 0.9. Even if it first improves as well, the validation accuracy varies more before stabilizing at 0.85–0.9, indicating some overfitting. The model's propensity to perform well on training data but less consistently on unseen data is highlighted by this difference between training and validation accuracy in the latter epochs.

The loss graph shows a comparable trend. The model's predictions are getting increasingly accurate in relation to the training data while the training loss steadily declines. Conversely, the validation loss initially drops but exhibits higher variance and does not follow the same smooth decline as the training loss, fluctuating around 0.2-0.4 in the later epochs. This divergence between training and validation loss further supports the presence of overfitting, where the model captures noise in the training data rather than generalizable patterns. To enhance the model's generalization, techniques such as regularization, data augmentation, or early stopping could be employed.



(a) **(b)**

Fig. 6 *Performance visualization of the SqueezeNet model (a) Visualization of accuracy result; (b) Visualization of loss result*

Precision indicates the accuracy of the model's positive predictions. For instance, a precision of 0.79 for Black Sigatoka signifies that 79% of the instances classified as such were truly Black Sigatoka. Recall, on the other hand, reflects the model's ability to identify actual positive cases. A recall of 0.98 for Black Sigatoka means the model correctly classified 98% of the actual Black Sigatoka instances in the data. Finally, the F1-score provides a balanced view by combining both precision and recall. An F1-score of 0.87 for Black Sigatoka suggests good overall performance for this class.

In overall, the SqueezeNet model performed well in classifying all three classes. The Healthy class achieved the highest F1-score (0.99), demonstrating exceptional accuracy in identifying healthy plants. While Black Sigatoka classification was also strong (F1-score of 0.87), Fusarium Wilt showed a slightly lower F1-score (0.83), indicating some difficulty in correctly classifying this particular disease.

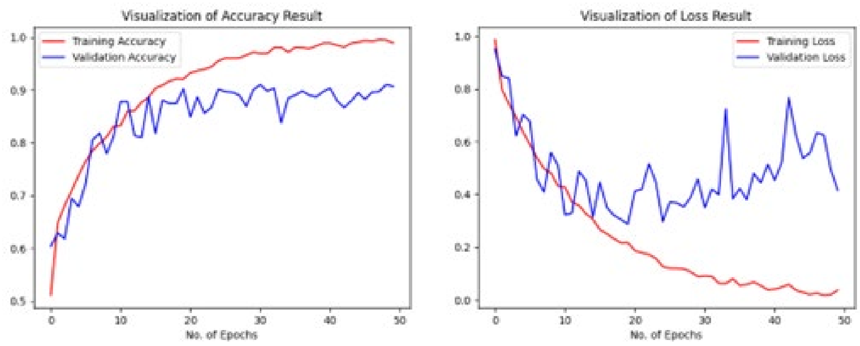
4.2 Performance of AlexNet Algorithm Model

Fig. 7 depicts the training performance of a convolutional neural network (CNN) called AlexNet. These curves track the model's accuracy and loss over epochs, which represent complete cycles through the training data.

The blue curve shows training accuracy, indicating how well AlexNet classifies images in the training set after each epoch. Ideally, this curve should steadily rise as the model learns. The orange curve represents training loss, reflecting the difference between the model's predictions and the actual labels. In general, we expect the training loss to decrease as the model improves its understanding of the data.

While the increasing accuracy and decreasing loss suggest AlexNet is learning effectively, these metrics alone may not guarantee good overall performance. The model might be overfitting, meaning it memorizes the training data too well but struggles with unseen examples.

Therefore, to get a more complete picture, it's crucial to evaluate AlexNet on a separate validation dataset. This helps assess how well the model generalizes new data and avoids overfitting.



(a) **(b)**

Fig. 7 *Performance visualization of the AlexNet model (a) Visualization of accuracy result; (b) Visualization of loss result*

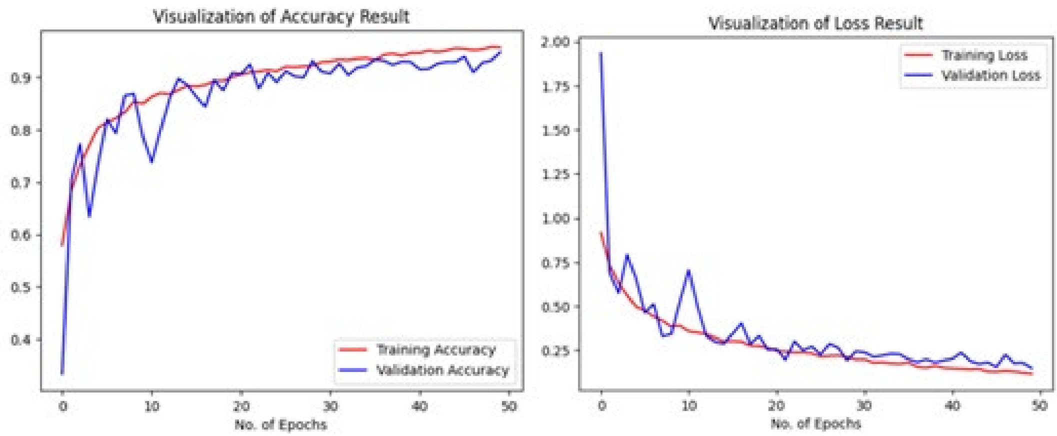
This model did a good job of finding Black Sigatoka images with 91% precision and made just few mistakes along the way. A recall of 0.91 for Black Sigatoka signifies that the model correctly classified 91% of the actual Black Sigatoka instances present in the data. In other words, it tells us how good the model is at capturing all the relevant cases. An F1-score of 0.92 for Black Sigatoka suggests the model achieved a good balance between these two metrics, performing well overall in classifying this particular class.

Overall, the AlexNet model achieved good performance in classifying the three classes in the dataset. It has the highest F1-score (0.97) for the Healthy class, indicating very good performance in correctly identifying healthy plant instances. The model also performed well on Black Sigatoka (F1-score of 0.92) and Fusaruim Wilt (F1-score of 0.91). The F1-scores are all similar across the classes, suggesting the model didn't favor any particular class and performed consistently well on all three.

4.3 Performance of MobileNet Algorithm Model

Fig. 8 depicts the graphs showcasing the accuracy and loss of the MobileNet model trained. Within 40 epochs, the model attains 99% training accuracy, demonstrating its rapid convergence. A larger number of input datasets and epochs may improve performance even more. Since the training dataset has more samples than the validation dataset, the training accuracy curve fits the training dataset better and is smoother than the validation accuracy curve. Both training and validation losses start to decline and settle after around 40 epochs, indicating a perfect fit that avoids either overfitting or underfitting.

The model's efficacy in accurately classifying the plants is demonstrated by the high classification accuracy of the confusion matrix as shown in Fig. 9 for plant disease prediction, where the diagonal elements are noticeably larger than the off-diagonal ones.



(a) **(b)**

Fig. 8 *Performance visualization of the MobileNet model (a) Visualization of accuracy result; (b) Visualization of loss result*

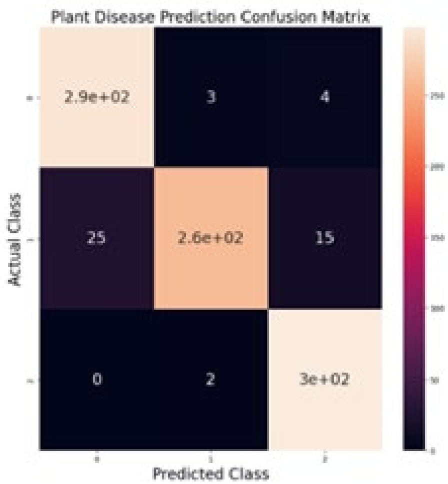


Fig. 9 *Confusion matrix for plant disease prediction using MobileNet*

Overall, the MobileNet model achieved good performance in classifying the three classes in the dataset. It has the highest F1-score (0.97) for Black Sigatoka and Healthy class, indicating very good performance in correctly identifying Black Sigatoka and healthy plant instances. Its performance on Fusaruim Wilt was slightly lower (F1-score of 0.92). This means the model had a bit more difficulty correctly classifying Fusaruim Wilt compared to the other two classes.

4.4 Comparison in Performance Between the Models

By comparing the models trained with different algorithm, it shows that MobileNet has the best performance with a higher validation accuracy of 94.89% and a lower validation loss of 0.1483. Besides, the classification results of the models also show that the MobileNet model has the highest accuracy of 0.95 and the highest average precision in classifying the classes.

MobileNet appears to deliver the best accuracy results due to the lengthy training time required by SqueezeNet and AlexNet are tabulated in Table 2 and 3. Additionally, MobileNet's compact model size makes it ideal for resource-constrained systems while also maintaining a relatively high level of accuracy. SqueezeNet and AlexNet also achieved good training accuracy. However, it is necessary to evaluate the model's performance on a separate validation dataset to assess how well it generalizes to unseen data and avoid overfitting.

Table 2 *Training time for SqueezeNet, AlexNet and MobileNet*

Algorithm	Time (minute)
SqueezeNet	288
AlexNet	348
MobileNet	292

Based on Table 3, the MobileNet model appears to be the best-performing model for classifying the three plant health classes (Black Sigatoka, Fusarium Wilt, and Healthy) compared to AlexNet and SqueezeNet.

MobileNet achieves the highest F1-score (0.97) for Black Sigatoka, whereas AlexNet gets 0.92 and SqueezeNet gets 0.87. For Healthy class, SqueezeNet has a score of 0.99, while both AlexNet and MobileNet have a score of 0.97. Even for Fusaruim Wilt, which seems to be the most challenging class for all models, MobileNet has a score of 0.92, while AlexNet gets 0.91 and SqueezeNet gets 0.83.

The F1-score considers both precision and recall, making it a good indicator of a model's overall performance. A high F1-score suggests the model is good at identifying the correct class (high precision) and avoiding false positives (high recall).

Table 3 *Precision, recall and F1-score performance of SqueezeNet, AlexNet and MobileNet on banana leaf disease*

Disease Type	Algorithm	Precision	Recall	F1-score	Accuracy
Black Sigatoka	SqueezeNet	0.79	0.98	0.87	0.90
	AlexNet	0.91	0.91	0.92	0.94
	MobileNet	0.92	0.99	0.97	0.95
Fusarium Wilt	SqueezeNet	0.99	0.71	0.83	0.90
	AlexNet	0.91	0.91	0.91	0.94
	MobileNet	0.98	0.87	0.92	0.95
Healthy	SqueezeNet	0.97	1.00	0.99	0.90
	AlexNet	0.97	0.98	0.97	0.94
	MobileNet	0.94	0.99	0.97	0.95

5. Conclusion

MobileNet achieves significantly higher accuracy than both AlexNet and SqueezeNet, offering a crucial advantage: efficiency. MobileNet gets good results while using fewer building blocks (parameters) compared to AlexNet and SqueezeNet. This is an advantage if you have limited computer power or need a faster model that can run in real-time.

MobileNet stands out not just for its accuracy, but also for its efficiency. It packs a punch with a smaller number of parameters compared to other models, making it run smoothly on devices with limited processing power like embedded systems. This lightweight design opens exciting possibilities for the future. Imagine deploying MobileNet on smartphones or drones for real-time plant disease diagnosis in fields or even integrating it into smart greenhouses for automated monitoring. With further research and expansion to encompass a wider range of crops and diseases, MobileNet has the potential to revolutionize the way we monitor plant health.

This research on banana leaf disease detection paves the way for exciting future advancements. By expanding the dataset to include a wider variety of diseases, the mobile application's diagnostic capabilities could become even more robust. Imagine the impact – farmers wielding smartphones, not just identifying problems, but receiving targeted treatment suggestions right there in the field. This integration of disease detection and treatment recommendations within the app could be a game-changer for banana crop health.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *Chong Mun Zheng, Nik Shahidah Afifi Md Taujuddin;* ***data collection:*** *Chong Mun Zheng;* ***analysis and interpretation of results:*** *Chong Mun Zheng, Nik Shahidah Afifi Md Taujuddin, Suhaila Sari, Zarina Tukiran;* ***draft manuscript preparation:*** *Chong Mun Zheng, Nik Shahidah Afifi Md Taujuddin, Suhaila Sari, Zarina Tukiran, Ahmad Raqib Ab Ghani. All authors reviewed the results and approved the final version of the manuscript.*

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