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Beans Leaf Diseases Classification Using MobileNet Models

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ABSTRACT In recent years, plant leaf diseases has become a widespread problem for which an accurate research and rapid application of deep learning in plant disease classification is required, beans is also one of the most important plants and seeds which are used worldwide for cooking in either dried or fresh form, beans are a great source of protein that offer many health benefits, but there are a lot of diseases associated with beans leaf which hinder its production such as angular leaf spot disease and bean rust disease. Thus, an accurate classification of bean leaf diseases is needed to solve the problem in the early stage. A deep learning approach is proposed to identify and classify beans leaf disease by using public dataset of leaf image and MobileNet model with the open source library TensorFlow. In this study, we proposed a method to classify beans leaf disease and to find and describe the efficient network architecture (hyperparameters and optimization methods). Moreover, after applying each architecture separately, we compared their obtained results to find out the best architecture configuration for classifying bean leaf diseases and their results. Furthermore, to satisfy the classification requirements, the model was trained using MobileNetV2 architecture under the some controlled conditions as MobileNet to check if we could get faster training times, higher accuracy and easier retraining, we evaluated and implemented MobileNet architectures on one public dataset including two unhealthy classes (angular leaf spot disease and bean rust disease) and one healthy class, the algorithm was tested on 1296 images of bean leaf. The obtained results showed that our MobileNet model achieves high classification performance for beans leaf disease, the classification average accuracy of the proposed model is more than 97% on training dataset and more than 92% on test data for two unhealthy classes and one healthy class.

INDEX TERMS MobileNet, tensorflow, deep learning, beans leaf, disease classification.

I. INTRODUCTION

Beans is one of the most widely consumed seeds in the world and it is an important crop worldwide, 30% of the crop is produced by small farmers in Latin America and Africa [1], beans are an important source of protein that offer many health benefits, despite its significance, beans plants are susceptible to various diseases, some of these disease caused by the fungus organisms, while others are bacterial [2]. Hence, bean production is very affected by diseases such angular leaf spot disease and bean rust disease, various types of pesticides are used to kill pathogens, for instance, angular leaf spot disease and bean rust disease can be controlled using fungicides, biological control and cultural practices such as inter cropping, optimum plant spacing and use of soil amendments that promote soil health and plant nutrition [1]. However, the excessive and widespread use of these chemicals can harm human health as well as the environment, for this reason the identification and classification of plant leaf diseases still an important role in agriculture. Therefore, an automatic system needs to be developed to control this disease very early, identification of crop diseases using some automatic techniques is very useful as it decrease the work of supervision especially in big fields of production, one such technique is the automatic classification of bean leaf diseases using deep learning models, automatic classification of beans leaf diseases is an important research topic performed to provide benefits to the farmer as it is important in controlling large fields of crops and at a very early stage and very rapidly. The work will help then to solve farmers problems of plant's

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disease identification, it will thus help them cure the plant's disease in early stage and will thus increase the quality and the quantity of crops, and therefore help in increasing farmer's profit.

In this paper, we have proposed a new method to classify beans leaf diseases into their classes by using MobileNet which is a convolutional neural network that provides an efficient models for mobile and applications, and by using beans leaf images. The proposed method was based on MobileNet with open source library TensorFlow and based on an accurate comparison and evaluation of MobileNet architectures (hyperparameters and optimization methods) that defines smaller and more efficient MobileNets model, the effectiveness of different architectures were compared and evaluated in order build effective model that can easily classify disease into their classes. In the current study we have used public dataset including two classes of beans leaf disease and one healthy class, the datasets used is a set of leaf images taken in the field in different regions by AI lab in cooperation with the National Crops Resources Institute (NaCRRI) [3], in this public dataset the data separated into three classes such as Healthy class with 428 examples, Angular leaf spot with 432 and the last class is Bean rust with 436 examples.

Due to the wide cultivation of beans crops, it is susceptible to diseases which in turn affects its production, this is the motivation that recognition of leaves unhealthiness is the solution for saving the beans crops and productivity, the objective of this work then is to develop an automated model capable of classifying and identifying disease type based on MoblieNet, beans leaf images and based on an efficient network architecture in order to build an accurate models that can be easily classified bean leaf disease into their classes, we evaluated and compared MobileNet architectures using single public dataset and then comparing their results for classification of bean leaf disease to find the best usable architecture and optimum classification results, in order to achieve this comparison of the effectiveness of different architectures, all the parameters have to be controlled under the same conditions using the same dataset. Furthermore, this paper proposed an efficient Mobile architecture in order to build very small, low latency models that can be easily matched to the design requirements for object disease classification in mobile applications. On the other hand, to get a clear insight about our classification resluts, the model was trained using MobileNetV2 architecture under the same controlled conditions as MobileNet to check if we could get high performance.

The problem of comparing and evaluating MobileNet architectures in order to classify plant leaf disease using single dataset is an important one in a number of applications and there are some unclear benefits of effectively comparing different experiments such as high performance, longer life and easier retraining. Therefore, an accurate system is designed to help classify beans leaf diseases and give aclear idea about some problems of automating plant leaf disease classification using MobileNet model architectures and single public dataset. The performance of the model has been analysed based on various parameter such as training accuracy, validation accuracy, loss and validation loss. To meet the input requirements of MobileNet and MobileNetV2 which is an improved version of MobileNet, the input image size is resized to 128×128 pixels. The rest of the paper organized as follows: A literature survey about the existing work were discussed in existing work section, discussion about the dataset and system configuration and training process were presented in research materials and methods section, the experimental setup and result discussion were presented in result and discussion section, and followed by conclusion.

II. EXISTING WORK

The automatic classification of diseases through images has got a great interest from researchers over the past few years. However, despite the efforts done, these diseases remain so far a critical challenge to sustainable agriculture. Moreover, there is still a great need for a serious procedure by a large team of specialists to continuously monitor these diseases for early stage, because most of the current disease classification and detection methodology is only a visual observation by experts for detecting plant diseases, but in recent years it has been evident that deep learning models with different approaches are very effective in classifying diseases.

Several studies have been performed using deep learning based models for classification and detection of plant leaf diseases in different crop species such as the approach presented by Liu *et al.* in [4] which was performed using CNN to identify apple leaf diseases (97.62% accuracy), Chen *et al.* in [5] also presented their study using the CNN model to identify tea leaf disease (90.16% accuracy), Brahimi *et al.* in [6] introduced another approach on classification and visualization of symptoms for tomato disease, they used AlexNet and GoogLeNet as a model for deep learning (97.3–99.2% accuracy). Shijie *et al.* in [7] have proposed a study for 10 different tomato crop diseases using VGG16 with MSVM, they reported an accuracy of 89% and they got training of fine-tuned models in a longer time, Picon *et al.* in [8] presented a method for crop disease classification in the wild, the method was found to be efficient in classifying trained datasets and based on deep convolutional neural networks for mobile capture device, the study of Picon et al reported an accuracy of 96%. Richey *et al.* in [9] have presented a study to classify the various maize crop diseases by using a mobile- app-based technique employing a DL-based model namely ResNet50, the model in this study has better generalization power and reported performance accuracy of 99%, but this method may not work well for all mobile phones due to processing power and battery consumption requirements. Barbedo in [10] proposed an automated system for plant pathology using GoogleNet model, Barbedo in this study have presented various issues and parameters that affect the efficiency of the network using mutliple crops, he got an accuaraccy of 80,75%. Agarwal *et al.* in [11] presented a CNN-based architecture to classify the tomato crop disease, the study is computationally efficient and reported an accuracy of 91.2%, the method of this study suffers from the issue of overfitting over a small number of classes. One of the interesting approaches followed by some researchers is to use the CNN based models. A study by Liang *et al.* in [12] compared the performance of using original CNN based model and CNN with SVM for the identification of rice disease, the performance of both techniques was approximately similar with an accuracy of 95.83% for CNN and 95.82% for CNN with SVM. Pantazi *et al.* in [13] have presented a method for plant disease classification using the LBP algorithm together with the SVM classifier, the main advantage of this method was that the model has better generalization power, but the classification performance degrades over noisy samples. Aravind *et al.* in [14] have proposed a study to classify Grape diseases by using AlexNet deep learning model, the study showed an improvement in accuracy of 1.61% compared to the original AlexNet, the classification performance of three disease achieved an accuracy of 97.62%. Sembiring *et al.* in [15] have presented a method for tomato plant disease classification based on leaf images, they employed a lightweight CNN for tomato leaf disease classification, Sembiring et al study was computationally efficient but only evaluated for tomato leaf disease classification and not robust to other scenarios. Chouhan *et al.* in [16] have presented a study for leaf disease segmentation and classification, the study was focused upon the leaf disease segmentation and classification for Jatropha Curcas L. and Pongamia Pinnata L. respectively. In this study Chouhan SS et al proposed a Hybrid Neural Network incorporated with Superpixel clustering, based on the features like color, texture, and shape and by using different algorithms the images were classified among different classes, they achieved a high segmentation results. Chouhan *et al.* [17] in other study proposed an automated method for plant leaf disease (foliar galls) detection and classification, the proposed method named as IoT_FBFN using Fuzzy Based Function Network (FBFN), the FBFN network having the computational efficiency of the fuzzy logic and learning adaptability of the neural network has been adopted for detecting the galls present on the leaf of Alstonia Scholaris, FBFN has the computational efficiency of the fuzzy Logic and adaptive learning were adopted for detecting the galls present on the leaf of Alstonia Scholaris. Singh *et al.* in [18] proposed an appropriate method for diagnosis of disease and its symptom, the proposed method was based on a multilayer convolutional neural network (MCNN) for classification of Mango leaves infected by the Anthracnose fungal disease. The objective was to create a system for an early solution of this problem, the performance of the proposed method is reported an accuracy of 97.13%. Chouhan *et al.* in [19] presented a method named as bacterial foraging optimization based radial basis function neural network (BRBFNN) for identification and classification of plant leaf diseases, the proposed method uses Bacterial Foraging Optimization (BFO) to assign optimal weight to Radial Basis Function Neural Network (RBFNN), this method was efficient in terms of computational for identification and classification of diseases from plant leaves but for this study, they have worked with only fungal diseases. On the other hand, there are other studies that used MobileNet model such as classification of tomato leaf diseases using MobileNet V2 (90% accuracy) presented by Siti Zulaikha *et al.* in [20], Vinutha *et al.* in [21] introduced Crop monitoring study using MobileNet models to identify 8 crop species and 15 labelled diseases based on training deep convolutional neural network, the trained model achieved an accuracy between 90% and 99% on the testing dataset.

MobileNet is trained on the ImageNet datasets for object detection and classification with TensorFlow library, comparing TensorFlow to traditional neural network, it only uses a small amount of data to train the model, and achieving high accuracy with short training time, TensorFlow was created by Google to specialize in machine learning applications, it provides comprehensive learning lessons for new classifications by imparting learning. TensorFlow got much attention in the area of machine learning all over the world because it's characterized by a high flexibility and accessibility and a great performance.

MobileNets is one of the pretested models on TensorFlow, to speed up the use of researchers in different fields, it has been improved on various structures, after Inception-v1, Inception-v2 and Inception-v3. MobileNet in this study has reported a successful model used for image classification, the performance of MobileNet with Beans leaf diseases is analyzed and a very satisfactory classification result is obtained. The analysis of existing methods employed for crop disease detection is presented in Table 1.

From the literature in table 1, it is clear that deep learning models with different concepts are effective in different crops for disease classification, but nevertheless, studies of a few vital crops were not found in the literature especially those using beans crops. Furthermore, due to the absence of this type of study on bean crops, and due to the wide prevalence of beans crops, we pay more attention to beans leaf disease classification in order to improve the yield and quality of beans crops, knowing that beans are one of the main crops that are widely consumed as an important source of nutrition. In this study, two major diseases of beans have been considered, for applying MobileNet for this classification problem, it has the capability to learn more complex features as more convolution layers are in the stack with smaller filter sizes compared to study using AlexNet or GoogLeNet because MobileNets are optimized to become small and efficient by compromising on the accuracy aspect, in the studies [20], [21], Authors used MobileNet to identify and labelled leaf diseases based on training deep convolutional neural network, in both studies validation accuracy remains low, meaning that the network is overfitting, and it retains features identified in the training images that do not primarily help it classify the diseases, this can be related to the MobileNet architecture (hyperparameters and optimization methods) used which means the performance achieved at least is biased in some way and cannot be

TABLE 1. Comparison of existing techniques.

References	Author	Plant name	Deep learning model	Performance	Approach
[4]	Liu et al	Apple	CNN	Accuracy=97.62%	Training from scratch
[5]	Chen et al	Tea	CNN	Accuracy=90.16%	Training from scratch
[6]	Brahimi et al	Tomato	AlexNet,GoogLeNet	Accuracy=97.3–99%	Transfer learning
[7]	Shijie et al	Tomato	VGG16	Accuracy=89%	Transfer learning
[8]	Picon et al	Wheat	ResNet 50	Accuracy=96%	Training from scratch
[9]	Richey et al	Maize crop	ResNet50	Accuracy=99%	Training from scratch
[10]	Barbedo	Multiple(Different crops of fruits, vegetables pulses)	GoogLeNet	Accuracy=87%	Transfer learning
[11]	Agarwal et al	Tomato	CNN	Accuracy=91.2%	Transfer learning
[12]	Liang et al	Rice	CNN	Accuracy=95.83%	Training from scratch
[13]	Pantazi et al	Multiple	LBP algorithm together with the SVM	Accuracy=95%	Training from scratch
[14]	Aravind et al	Grape	AlexNet	Accuracy=97.62%	Transfer learning
[15]	Sembiring et al	Tomato	Lightweight CNN	Accuracy=97.15%	Transfer learning
[16]	Chouhan et al	Jatropha Curcas L. and Pongamia Pinnata L.	Hybrid neural network and seven different Machine Learning techniques	accuracy = $\approx$ 99.6%	Training from scratch
[18]	Singh et al	Mango leaves	MCNN	Accuracy=97.13%	Transfer learning
[20]	Siti Zulaikha et al	Tomato	MobileNetV2	Accuracy=90%	Transfer learning
[21]	Vinutha et al	Multiple(8 crop species and 15 labelled diseases)	MobileNet	Accuracy=90%-99%	Transfer learning

the optimum result but can be improved. In contrast to our study, we have proposed a new method for classifying bean leaf diseases into their classes, the proposed method is based on an efficient network architecture in order to build very small and low latency models that can be easily classified the disease into their classes, we evaluated and compared MobileNet architectures to get the best usable one to be used in beans leaf disease classification, our approach shows better plant leaf classification performance compared to the models in previous studies. In [20], [21] the performance accuracy of both study are 90% and 90-99% respectively on training dataset, which is lower than the current study, in the current study the performance achieved an average accuracy of 100% on training dataset and 98.49% on validation dataset especially when we used Adam optimizer.

In our study, features from different layers including fully connected layers were analyzed and in the some cases this study was found to improve results which is better comparing with the previous studies. Moreover, the effectiveness of different architectures were used and evaluated, In addition to that, our model was trained using MobileNetV2 architecture under the same controlled conditions as MobileNet, and the goal is to check if we can get higher performance and easier retraining. The performance result will be discussed in result and discussion section.

III. RESEARCH MATERIALS AND METHODS

In this section, the methods used in the study, the datasets and the performance evaluation criteria of the proposed method are detailed.

A. DATASET AND SYSTEM CONFIGURATION

In this study, great importance is given to the factors and to different pests and pathogens that causes severe damage to the crop [22]. As a result, we have used three classes (as shown in Figure 1), and we identified two major diseases described in Table 2. The beans losses are huge because of these two major diseases, detecting and curing these diseases at the primary stage helps save a lot of effort and time.

The dataset used in this study is a public dataset presented by tensorflow and was choosen from GitHub [3], this public dataset was annotated by experts from the National Crops Resources Research Institute (NaCRRI) in Uganda who determined for each image which disease was manifested, collected by the Makerere AI research lab and released on Jan 20, 2020, it comprised of the beans crop leaf images taken from the real field, this dataset contains 1296 images split into three classes: 2 disease classes and one healthy class as shown in the table 2. Therefore, in this experiment the dataset separated into three classes which are Angular leaf spot class, Healthy bean class and Bean rust class (see Table 2 and Figure 1) with 80% training and 10% testing and 10% validation.

Samples of the leaf images according to the used classes are shown in Figure 1. The image of this public dataset was taken by a smartphone camera on the farm, so in our study condition to provide a suitable trainer model to improve disease prediction, we transformed every image in this dataset into 128-by-128 pixels according to the input requirement of MobileNet.

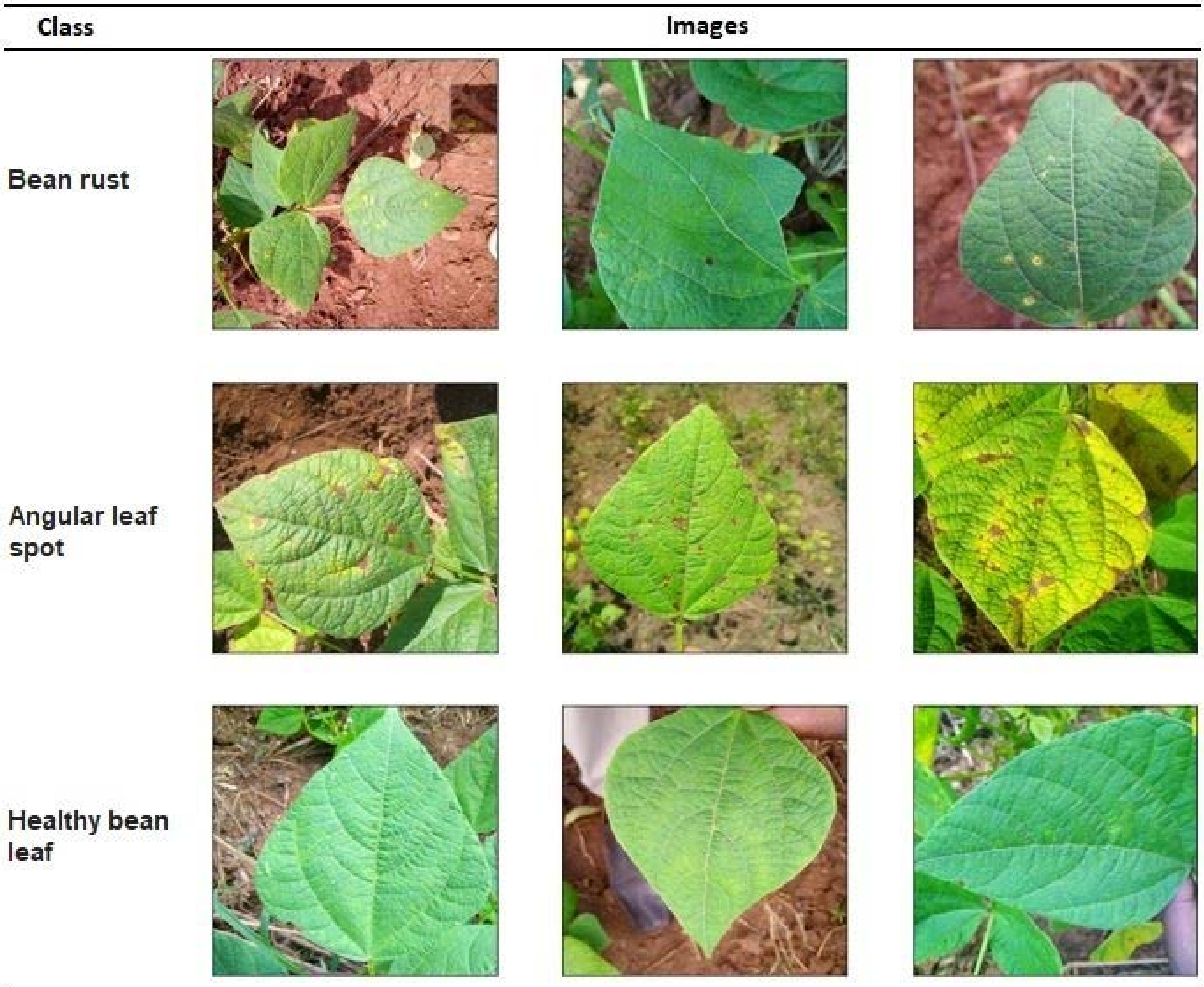

FIGURE 1. **Beans leaf diseases classes some example images.**

In this public dataset each image associated by experts from (NaCRRI) who determined for each image which disease was manifested and associated with exactly one condition (healthy, angular leaf spot disease, or bean rust disease). Some leaf image backgrounds consist primarily of other overlapping leaves of the same plants as shown in figure 1, and the circumference of images also differs within groups of images within the same category. The dataset will be trained using MobileNet architectures within the CNN model, and the results evaluated according to four different performance evaluation criteria. Recall, Precision, Accuracy and F1-score.

The experimental results were tested using Dell N-series lap-top: processor 2.5GHz Intel i6, with 6 GB memory, and based on the MobileNet model with python and TensorFlow open source library. All the implementations were performed using Google Colab on a personal computer with GPU, such kind of GPU specification is vital for reducing the learning time from days to a few hours, GPU support is very significant in the processing of ample examples in each iteration of learning. Table 2 show a description of the used dataset.

TABLE 2. **Bean leaf diseases description.**

Class	Description	Dataset
Bean rust	**Caused by:** the fungus Uromyces Appendiculatus. **Symptoms:** Rust can occur on all above-ground parts of the plant, but rust spots are most numerous on the un-dersides of leaves.	436
Angular leaf spot	**Caused by:** it is a bacterial disease caused by Pseudomonas syringae pv. lachrymans. **Symptoms:** usually first appear as water-soaked lesions bound by the veins of the leaf, so they are angular in shape. the lesions may turn yellow and then brownand the leaf tissue may tear.	432
Healthy class	-	428

B. IMPLEMENTATION

This section focuses on the experimental setup of bean disease model using MobileNet with TensorFlow framework, to perform the implementation of DL architectures, various

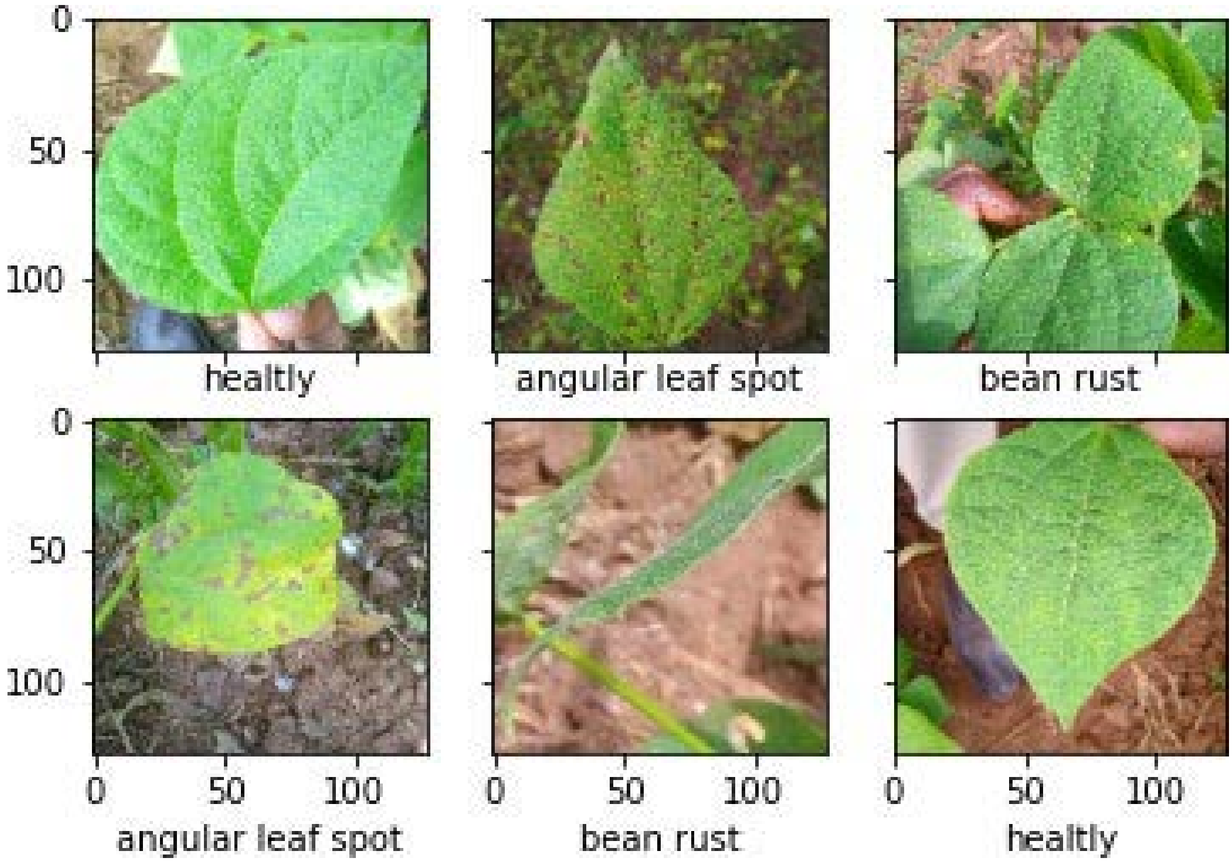

FIGURE 2. A glimpse of labeled dataset.

steps are needed; begin from the dataset collection to performance analysis and classification, here the classification model is divided into different stages such as examine the data and build an input pipeline in order to develop a classifier that can predict whether the bean leaf have been affected by a disease or not, we've also labeled the data (as shown in Figure 2) since the learning method of MobilNet fits into administered learning in deep learning. Similarly, we build validation and test pipeline using similar transformations, it is a good idea to check the disease class imbalance and see if there is a class with significantly fewer samples than the other disease class. But in the current study, we used a public dataset which previously had almost balanced classes and separated into three classes which are Angular Leaf Spot, Healthy class and Bean Rust. In this study, MobileNet has 8 convolution layers designed for image classification, and every image is used multiple times through training process, during model training, the learning algorithm will experience each training batch precisely one time during one epoch, and toward the finish of every epoch, it will also rate its performance on the validation set.

In the current study, the training set size is 1034 images and each batch contains 32 examples, so we will have 33 batches in each stage. For now, we have set the number of epochs to 100, although in practice the model should be stopped when the accuracy and loss have stabilized, we should see the training and validation loss go down with each epoch. Regarding the hyperparameter settings of the current experiment architectures, we have used the filter size number to 10 with correlation 0.8 and 0.001 for weight decay as L2 regularization.

The classification results for this study were based on comparing and evaluating different architectures (hyperparameters, optimization methods) under a similar condition work in order to compare results excellently, performance metrics were applied to the classification of crop disease (beans leaf image), various classification techniques were also applied on the test data in the prediction, the obtained results will be discussed in the result section.

C. TRAINING PROCESS

In this study MobileNet models were trained in TensorFlow using different MobileNet architectures and five different optimizers namely adagrad, nadam, SGD, RMSprop and adam optimizer, with asynchronous gradient descent. However, compared to other models such as Inception, we found that the MobileNets use less regularization and based on depthwise separable convolution while Inception V3 for instance uses standard convolution, this results into lesser number of parameters in MobileNet, However, this results in slight decrease in the performance as well, so it is important to put a very little or no weight decay on the depthwise filters since there are few parameters in them. In other words, to train the large models, we use less data-organizing techniques like applying geometric transformations, because small models have less trouble. Actually, the size of the input to the network is also small, the output of the neural network is 3 classes labels of 1 crop.

The architecture of MobileNets is trained and tested using Python language with Tensorflow CPU library. In other side we used other method called MobileNetV2 [23] which is a convolutional neural network architecture which is based on an inverted residual structure, it is an improved version of MobileNet, the basis of the network remains the same, which is a detachable convolution. MobileNetV2 that was previously trained on ImageNet datasets used to extract features of fruit images in [24] have shown a great result. Figure 3 shows the components of the system where the dataset is used to train and test the proposed MobileNet V2 based on beans disease screening algorithm.

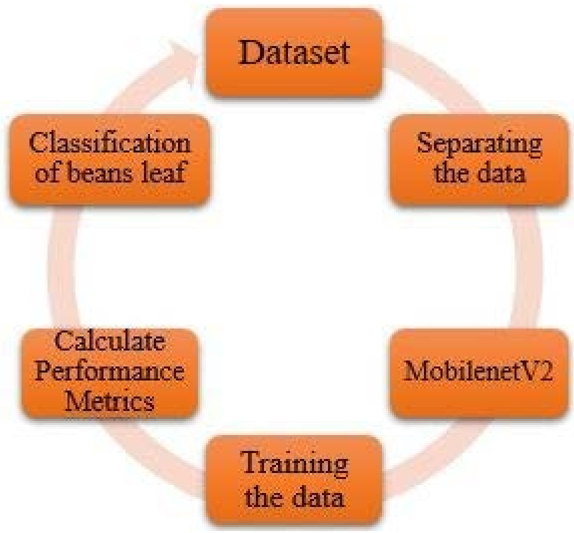

FIGURE 3. Major components of beans diseases classification using MobileNet V2.

IV. RESULT AND DISCUSSION

This experiment is based on a MobileNet model with the open source library TensorFlow, normal CPU-based Tensor- Flow is implemented using the Python platform, the data separated into three classes such as Healthy class with 428 examples, Angular Leaf Spot with 432 and the last class is Bean Rust with 436 examples, dataset used was separated into training, test and validation set with 1034 and 129 and 133 examples respectively, the goal is to build a strong deep learning model capable to distinguish between diseases in bean leaf.

In this experiment, the different architectures configurations of MobileNet and MobileNetV2 hyperparameters include batch size, optimizer selection, and learning rate are tested, this testing process was performed and compared sequentially, and each hyper parameter were tested separately to find the optimal architecture setting. In order to achieve this comparison of the effectiveness of different architectures, all the criteria were controlled under the same conditions (architecture, methods, hyperparameters,filter…), and using the same dataset, image were randomly selected for each group. Therefore, the performance varies according to the image selected and the architecture used.

The performance evaluation criteria of the proposed method and the obtained results of beans leaf disease classification are discussed in the following sections.

A. OPTIMIZATION METHOD

In this section we have used and tested five different optimizers (adagrad, nadam, SGD, RMSprop and adam optimizer) in the same experimental conditions (architecture, methods, hyperparameters, dataset…), then in order to obtain the optimum accuracy result among this five optimizer, we compared their results based on model accuracy and model loss using the training and validation set as shown in Table 3, among these five optimizers, and compared to the rest of the SGD optimizer and Adam's optimizer were distinguished with high performance and accuracy in the results of the classification of bean leaf diseases associated with three classes, both are more stable than the other optimizers, they don't suffer any decreases in accuracy. Therefore, we selected the both optimizers to be used in this experimental study based on MobileNet as shown Figure 4. Adam optimizer gives the best accuracy of 100%, followed by SGD optimizer that return the second high accuracy in classifying bean leaf diseases with accuracy of 99,94%. Table 3 shows the classification results of different optimizers we tested. Figure 4 describes the performance comparison of Adam optimizer and SGD optimizer based on accuracy, validation accuracy, loss and validation loss.

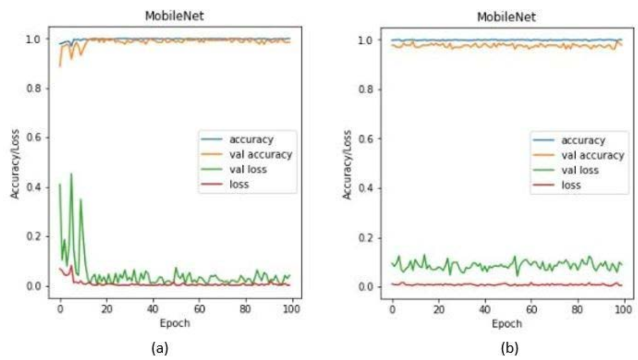

FIGURE 4. Comparison of accuracy and loss of two optimizer methods. (a) Adam, (b) SGD.

TABLE 3. Training and testing set accuracy and loss results of five optimizers.

optimizers	accuracy	val-accuracy	loss	val-loss
adam	1	0.9849	0.00078	0.0411
SGD	0.9994	0.9847	0.0095	0.0478
nadam	0.9990	0.9824	0,0254	0.0261
RMSprop	0.9924	0.9724	0.0334	0.2059
adagrad	0.9850	0.9699	0.0703	0.0869

B. LEARNING RATE

Selecting hyperparameters manually is time-consuming and error-prone, as the model changes, the previous selection of

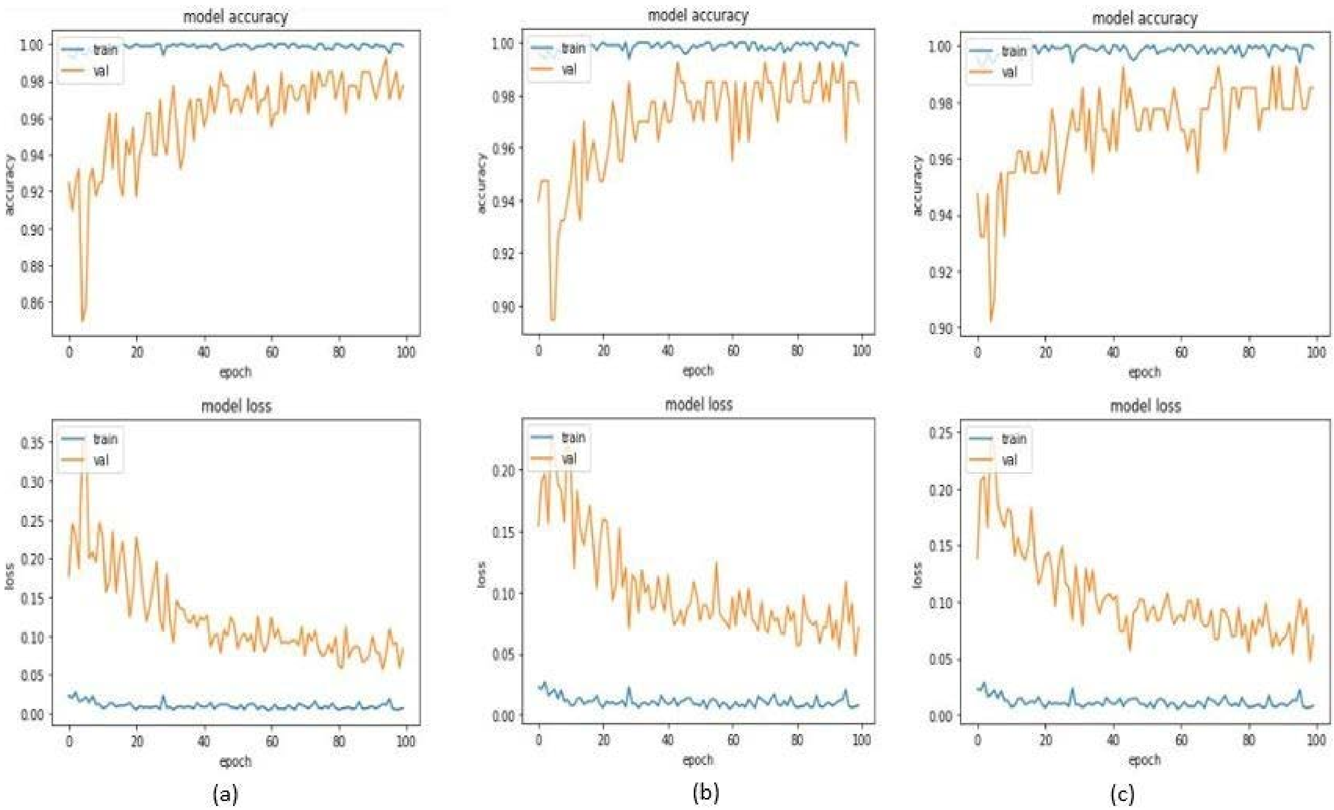

FIGURE 5. Testing accuracy and loss for different learning rates (a) 0.001, (b) 0.0001, (c) 0.00001.

hyperparameters may not be ideal, it is impractical to constantly perform new searches manually. Therefore, we automatically compared the performance of different learning rate for bean leaf disease classification using our Mobilenet model as shown in Figure 5, the goal of comparing different learning rate performance on our model is to powerfully aid disease classification in their classes.

Learning rate is one of the most important hyperparameter and especially when configuring neural network, it is used to evaluate the error gradient for the actual state of the model, and it's very important to controls how much the gradient model error will be used to update the current weights.

In this case study, we chose SGD optimizer as the essence for the test because of the difference observed once the rate is changed, and due to the high accuracy of the results obtained by this optimizer, Therefore, to illustrate how our model differs in optimal learning rate, here we performed a case study for each learning rate using our model architecture for classifying bean leaf disease. As shown in figure 5, we have tested three rate (0.01, 0.001 and 0.0001), and we selected the same number of training epoch to be used to test these three rates on MobileNet.

In table 4, the result shows that high accuracy is 99.90% and it's achieved when a learning rate of 0.001 is applied, while the lowest accuracy was obtained using 0.0001, the performance remains high in all cases, the accuracy is

TABLE 4. Accuracy and loss of various learning rates.

learning Rate	tr-accuracy	tr-loss	val-accuracy	val-loss
0.001	0.9990	0.0071	0.9774	0.0830
0.0001	0.9989	0.0080	0.9773	0.0714
0.00001	0.9987	0.0081	0.9850	0.0700

between 99.87% and 99.90%, and the loss ranges between 0.0071 and 0.0081, which means that the learning rate in our study did not affect the training accuracy much, and the performance did not depend on the size of the model. Table 4 presents the performance result for different learning rate, and Figure 5 describes the performance comparison of three different learning rate based on accuracy and loss.

C. BATCH SIZE

Batch size is a hyperparameter that controls the number of samples images to the network for one training iteration. In other word, it refers to the number of training examples used in a single iteration in the model, and it is very important while training, as shown in Table 5 we used and tested three batch sizes of 32, 64 and 128 to compare their classification accuracy, and for this example study we used 0.001 as learning rate, and 100 epoch.

During testing, we observed that minimal fluctuations in training error are observed when using the batch size method,

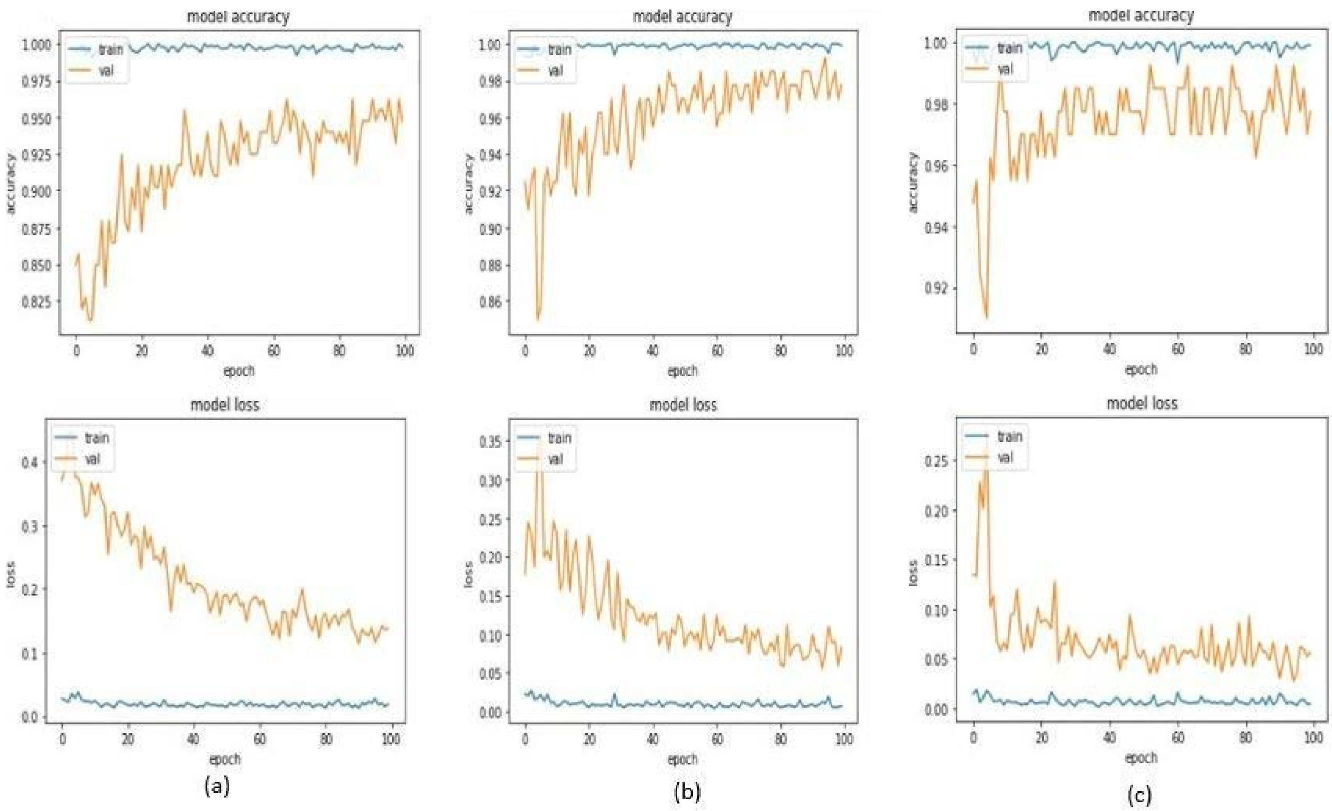

FIGURE 6. Testing accuracy and loss of different batch sizes: (a) 128, (b) 64, (c) 32.

but the bigger batch size will outcome to over generalization. Moreover, for the accuracy of classification we have used batch size 32, 68 and128, and we found that the high performance is obtained when using batch size 32 which give an accuracy value of 99.90%. In additionally, Figure 6 shows that the classification accuracy value in this study decreases once the batch size is increased from 32 to 128, which means that the batch size number should not be chosen too much and not too low and in such a way that the number of images remains about almost the same at each step of an epoch, keeping in mind that small batch sizes require small learning rates, and the batch size controls the accuracy of gradient error estimation when training networks. Table 5 provided a comparison of accuracy and loss using different batch sizes. Figure 6 depicts the same performance representation on a graph.

TABLE 5. Comparison of accuracy and loss in different batch sizes.

Batch Size	tr-accuracy	tr-loss	val-accuracy	val-loss
32	0.9990	0.0045	0.9774	0.0560
64	0.9989	0.0071	0.9773	0.0830
128	0.9978	0.0190	0.9474	0.1371

D. USING MOBILENET AND MOBILEV2 STRUCTURE

The accurate classfication of beans leaf diseases is essential for their prevention and control, and the goal of comparing and evaluating different architecture performance on a single public dataset is important in itself, because when models are evaluated and in preparation for comparisons finer details are recorded that comes in handy during retraining, the goal is to find the best classification model that fit both the data and business requirements.

In this section we have performed a test experimentt for beans leaf disease classification by using MobileNet and MobileNetV2 as an improvement over MobileNetV1 by using depthwise separable convolution as effective building blocks which have been shown to be successful model used for image classification, we used this as our base model to train with dataset and classify the images of beans leaf diseases. However, to satisfy the classification requirements the model was trained after modifying the output layer and the hyperparameter. In this case of study we have used the number of 100 epoch, 0.001 as a learning rate and 64 as a batch size. As shown in figure 7 it was very clear that our MobileNet model achieved a high average accuracy of 100% with 0.0112 of loss and during acceptable training times which is 173s on training dataset for 20 epoch. On the other hand, we used MobileNetV2 to check if we could get more faster training times and higher accuracy, and then the small parameter number requirements allowed MobileNetV2 to obtain a highly accurate classification result for bean leaf disease compared with MobileNe. Therefore, MobileNetV2 was very effective for object classification and faster than MobileNet with the same accuracy and lower loss value with only 0.0102, and with a short training time of 165s for 20 epoch.

The performance of accuracy is then used to measure classification performance, which is divided into three classes of Healthy bean leaf, Angular leaf spot disease and Bean rust disease, the performance here is based on loss and accuracy, as shown in Figure 7 training progress graph has been plotted to show and demonstrate MobileNet and MobileNetV2 performance in classifying bean leaf diseases, both architectures were implemented using accuracy, loss, validation accuracy, and validation loss.

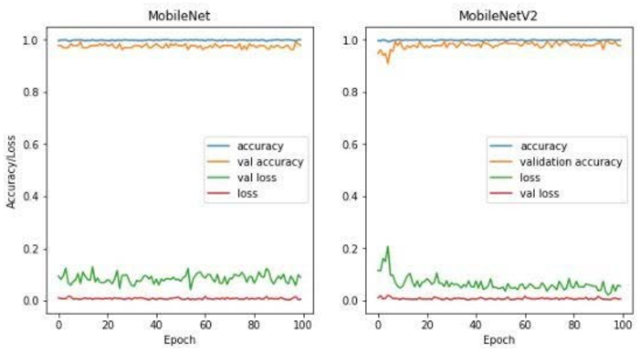

FIGURE 7. Testing accuracy and loss using MobileNet and MobileV2 Structure.

After training the model for 100 epochs, we found that the model converged at an accuracy between 99% to 100%, and it achieved a validation accuracy of 97.74%. Figure 8 shows the plot accuracy of the model at the end of every epoch.

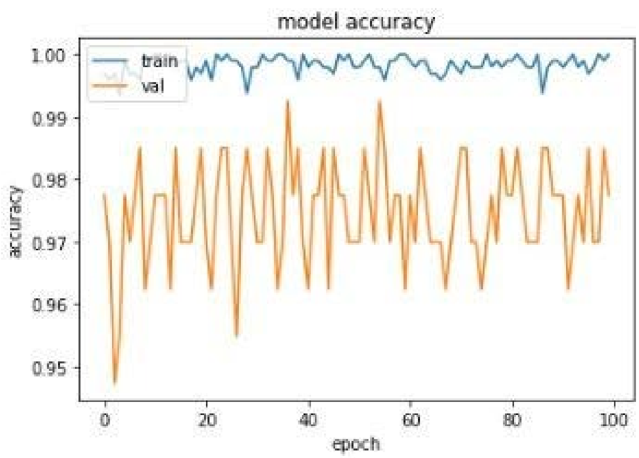

FIGURE 8. Accuracy result of simple classifier of the model.

In other hand, to gives a clear insight about the accuracy and about the ways in which our classification model is confused when it makes predictions, we have used the confusion matrix that create a summary of prediction results on a classification problem. Therefore, with two labelled sets (true and predicted) we summarized the results of testing the classifier that distinguishes between three classes (Healthy bean leaf, Angular leaf spot disease and Bean rust disease) of our model.

In these experiments, the model were trained using the same hyper-parameters mentioned before, and the architecture requires a few additional iterations to achieve closeness and stability within 100 epochs. So as was expected, the proposed method and the architecture trained with dataset image resulted an accuracy of 92.97% on test dataset including 128 images and combined from 3 different classes as shown in Figure 10. Furthermore, the model achieved 99.87% as a training accuracy and 97.44% as a validation accuracy of leaf disease classification. Figure 9 shows a confusion matrix that creates a summary of the classification model on three classes using beans leaf images.

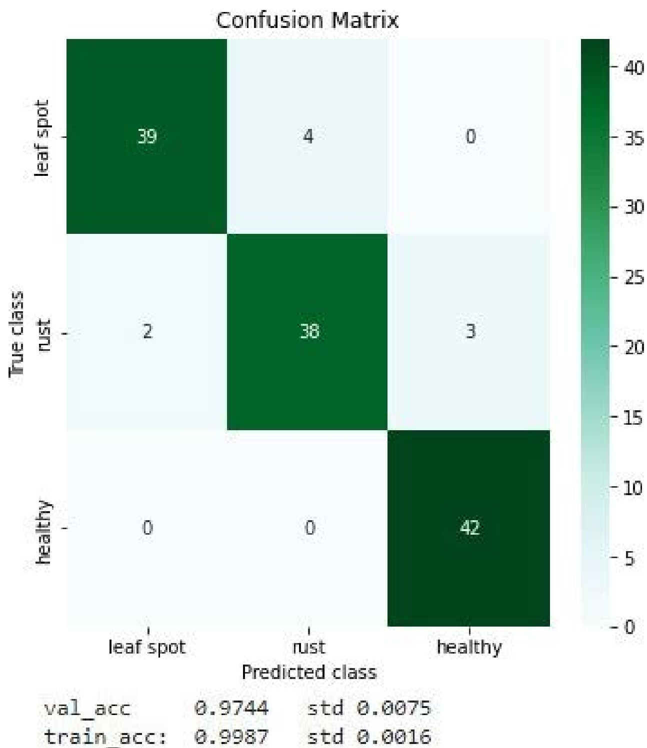

FIGURE 9. Confusion matrix for classification model.

Various performance metrics were used in this study to evaluate the performance of the model, each being precise to the MobileNet model deployed in this study. Therefore, for a better look at the study performance, we measured classification performance of the proposed system by using various metrics such as Accuracy, Recall, Precision and F1score.

Since we have all the necessary metrics for all the classes from the confusion matrix, we calculated the performance measures for these classes as shown in Figure 10.

	precision	recall	f1-score	support
0	0.9512	0.9070	0.9286	43
1	0.9048	0.8837	0.8941	43
2	0.9333	1.0000	0.9655	42
accuracy			0.9297	128
macro avg	0.9298	0.9302	0.9294	128
weighted avg	0.9297	0.9297	0.9291	128

FIGURE 10. The performance measures for three classes.

The classification performance evaluation resulted the highest accuracy as well as recall, precision and F1 score.

The precision, recall, F1 and support values for all the individual classes are shown in Figure 10, the average accuracy and weighted class wise accuracy is described too.

Our proposed model for beans leaf diseases classification were successfully implemented, analyzed and a very satisfactory performance classification result were obtained. The model is computationally efficient but only evaluated for beans leaf disease classification and not to other scenarios. Therefore, this method may not work well for all datasets, But if the other datasets are subsets of the same distribution and the samples were obtained independently and in identical fashion, then the model would yield great results as well.

V. CONCLUSION

The bean leaves can be affected by several diseases, such as angular leaf spot disease and bean rust disease which can cause big damage to bean crops and decrease its production, thus, treating these diseases in their early stages is needed to improve the quality and quantity of the product. In this paper we devloped an automatic model to classify and identify the type of disease based on MoblieNet, beans leaf image and based on an efficient network architecture, in order to build an accurate models that can be easily classified the disease into their classes. In this paper, we not only presented a method for classifying bean leaf disease but also we used, evaluated and compared the effectiveness of different architectures to find the best one to be used in beans leaf disease classification, a very satisfactory classification result is obtained, the result when compared with other methods, show that the proposed method achieves higher performance in terms of classifcation of plant leaf diseases, the best experimental result is obtained when our model is trained using adam optimizer, learning rate of 0.001 and batch size of 32 with training and validation set accuracy of 100% and 98.49% respectively, and the model achieved also an accuracy of 92.97% on 128 test data, similar to that, in this study the minimum training accuracy and validation accuracy were 98.50% and 94.74% respectively, which demonstrate the highest performance of the proposed method. Furthermore, as another result of this study, it was revealed that the classification training accuracy value decreases as soon as the batch size increases and the learning rate decreases.

We believe that the results obtained during this work can bring some inspiration to different similar visual recognition issues, and therefore the practical study of this work will simply extend to the classification problems of other plant leaf diseases.

In this study, we have worked with only beans leaf diseases, in the future, this work will be extended to work on different databases with dissimilar diseases like Bacteria, Viral, Fungal and Viruses.

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